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# Innovation and Collaboration networks: Assessing knowledge pipelines, knowledge flows and firm performance

**Thesis presented by Palina SHAUCHUK**

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Supervisor: Professor Michele CINCERA
Co-supervisor: Professor André SPITHOVEN

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CHAPTER I

# INTRODUCTION


## SUMMARY

*In this introductory Chapter the rationale for this research is explained and an overview of the thesis is provided. This chapter serves as a concise introduction to the subject of the knowledge base and knowledge pipelines in a metropolis as Brussels, as well as providing an insight into the policy driven empirical research with additional focus on the appropriate spatial level of analysis to highlight the spatial inequality of innovation. The objectives of the thesis are reviewed by giving an overview of the research questions and the main hypotheses related to them. The theoretical background used in this thesis is briefly outlined. The structure of the thesis can be summarised as follows. The second chapter provides basic information about data on patents and scientific publications, the construction of indicators based on patents and scientific publications, as well as guidelines for the compilation and interpretation of patent and scientific publication indicators. The third chapter focuses on the determinants of the efficiency levels across regions in Belgium at different spatial levels. The fourth chapter builds on the research made in the previous chapters and focuses on the analysis of the impact of patent collaboration networks on the output growth of R&D active companies in Belgium. The fifth chapter analyses the impact of different collaboration ties on the productivity of innovative companies in Belgium, measured in several ways through the innovation survey and in terms of patents. The conclusion reported in the last chapter summarises the main findings and highlight possible suggestions for future research.*

## 1.1 Context and research objectives

Regional innovation system (RIS) is an approach which analyses and grasps important aspects of regional clusters, referring to particular development tendencies in the building of networked innovation in regions. This is also a tool in policymaking that is necessary to support business competitiveness on a regional scale (Cooke, 1998). Besides, the concept of regional innovation systems has evolved into an accepted way of understanding the uneven spatial development of the knowledge economy. The concept clearly shows that both knowledge producers and exploiters are active in their own global networks, but the competitive advantage is created at the regional level through the interactions which create supporting institutions.

Studies on regional innovation policies are closely linked to those on regional innovation systems (Cooke, 1992; Asheim and Isaksen, 1997). The RIS concept appeared in the 1990s and was associated with the literature on National Innovation Systems, the contemporary debates on new economic geography and the policy relevant cluster theories. The role of regional innovation policy is to support the exchange and create new paths between different organisations, such as innovative vouchers, industry scholarships, or industrial departments. The approach of regional innovation systems suggests that the region is a key level at which innovative capacity is shaped and economic processes coordinated and governed. Nonetheless, not only technological and sectoral factors are essential in RIS, the regional dimension is of key importance. Regions differ in terms of their industrial specialisation pattern and their innovation performance (Breschi, 2000; Howells, 1999).

The new paradigm of local and regional development (OECD, 2009) stresses the identification and mobilisation of endogenous potential, where the regions are able to develop their own resources, human capital and innovative potential. Regional development is looking for strategies that apply previously unused economic potential that deal with sustainable development and human well-being. These strategies also rely on regional development agencies and require engaging a wider range of stakeholders and mechanisms to identify the key assets of the regional economy on which regional growth strategies are based. This new approach applies not only in economically strong areas but also in such areas as foreign direct investment and export (De Bruyne and Van Hove, 2013).

The spatial proximity is a key element in the resource perspective and the regional innovation system. The spatial proximity can strengthen the potential for interaction, collaboration, coordination, and contacts between firms and their R&D or innovation partners (Teirlinck et al., 2010). Hence the importance of the concept of localised learning. Localised learning shows how local conditions and spatial proximity between subjects allow the formation of distinctive cognitive repertoires and the impact on the formation and selection of skills, knowledge processes, products or activities. Localised learning explains regional economic specialisation, co-location to form clusters and reproduction over time (Maskell, 2001; Cooke, 2002). According to the resource-based view, it is recognised that specialised technological knowledge or known R&D providers are vital, but they are not necessarily available in the region. Organisations lacking specialised knowledge will require it regardless of their location (Teirlinck et al., 2010). Spatial, organisational, institutional, cognitive and social proximities are also considered as equally important proximities dimensions in the requirements from knowledge and technology transfer (Boschma, 2005).

The Brussels-Capital region can be seen as a “regional innovation system”. This system reveals the importance of an ecosystem approach based on the cooperation between differentiated types of actors localised in the same area (Caniëls and van den Bosch, 2011; Cooke et al., 1997; Iammarino, 2005; Moulaert and Sekia, 2003). This approach has become widely recognised by policymakers, referred to as the Triple Helix (Etzkowitz and Leydesdorff, 2000).

The other approach to the existence of knowledge pipelines highlights the functioning of the regional innovation system risks undermining the relevance of supra-regional flows (Bathelt et al., 2004; Leamer and Storper, 2001; Maskell et al., 2005). The purpose of this analysis is to combine these established approaches in an empirical analysis of the Brussels-Capital Region.

The research objectives of the **Chapter II** emphasise the different factors which are related to the knowledge base and knowledge pipelines in a metropolis such as Brussels. The knowledge base states the locational advantages in the Brussels Capital Region (BCR) that are instrumental in attracting innovative firms that contribute to localised learning and regional development in the long run. The purpose is to clarify the interrelatedness of Brussels actors within the region; i.e. to examine the nature, dynamics and governance of the regional innovation system for Brussels. Moreover, to focus the analysis on the nature of the relations with the hinterland. The link between the Brussels Capital Region and its hinterland is characterised by the role of the BCR as the European capital and it’s headquartered function. Patent and scientific publications are key indicators, even though they do not represent all knowledge produced, which are used to investigate the different factors related to knowledge base and knowledge pipelines.

The understanding of the innovation process has changed over time. Innovation models emphasise the relevance of networking activities and knowledge spillovers which are the mechanism of the formation of networks. R&D and innovation activities have always been recognised as key indicators on analysing knowledge economy. The recognition among researchers that R&D activities are unequally spread across space (Aydalot, 1985; Kleinknecht and Poot, 1992) leads us to the question of how and why R&D activities become effective and what are the primary means for their diffusion. To understand the reasons behind this phenomenon, we are interested in factors determining the location of R&D. Gassmann and von Zedtwitz (1999) argue that the location of new R&D is dependent on previous location decisions, which is defined by location factors. Therefore, the location of R&D activities is especially dependant on historical factors (Cornet and Rensman, 2001). Since stimulation of growth plays an important role, we have to emphasise the importance of attracting new R&D activities in the regions. Many factors determine the location of R&D, the most important being history, the supply of R&D labour, and the quality of the public knowledge infrastructure and knowledge transfer (Cornet and Rensman, 2001).

Despite widespread recognition of the uneven spatial distribution of R&D activities, the empirical literature on regional innovation systems neglects this spatial effect (Crescenzi, 2005; Fagerberg, 1994; Jaffe, 1989). This issue is currently questioned in several empirical studies that emphasize the uneven spatial distribution of R&D and their cooperation (Autant-Bernard and Chalai, 2013; Autant-Bernard et al., 2007; Aldieri and Tsintser, 2009; Barber et al., 2011; Hoekman et al., 2013; Cincera et al., 2006 and 2014). The main idea of this research is that R&D collaboration changes the spatial distribution of knowledge and in turn the territorial competitiveness of regions.

Our research explores the dynamism and change of R&D activities' spatial distribution. R&D activities are very much a functional phenomenon and the consequences in terms of past growth have determined the current relative position of the regions (**Chapter III**). Additionally, Chapter III extends the existing literature in several ways. Firstly, the analysis is based on lower spatial levels such as provinces, districts and city agglomerations which provide a clear view of a more detailed country profile of Belgium and its spatial disparities. Secondly, it compares the obtained results with previously investigated research about Belgium and provides its spatial differences. Finally, it assesses the output growth by using the Cobb-Douglas production function model, concerning the different spatial dimensions.

The concept of spillovers of knowledge from external sources may have an important impact on innovation processes and economic development which became increasingly recognised in the literature. The sourcing of external knowledge for innovation is a crucial process of a firm's innovation activities (Dahlander and Gann, 2010). The decision to search and obtain knowledge spillovers and form innovative partnerships is based on the necessity to complement the organisations' static resources through external knowledge linkages or innovative networks. However, external knowledge has to be integrated with the rare, and difficult to be copied by competitors', path-dependent specific firm resources (Barney, 1991; Kang et al., 2012). Following the same logic, the external knowledge decisions, made by organisations, are based on existing resources of the organisation. Quantitative research on external knowledge sourcing confirms that involving external sources of knowledge in innovation is a promising alternative for firms (Laursen and Salter 2014). Holcomb and Hitt (2007) discuss that the resource-based perspective looks explicitly at external knowledge linkages. The authors also state that if the organisation uses external knowledge that is lasting, unique, non-reproducible and beneficial, in turn, it facilitates the competitive advantage of the organisation.

Significant effort was made to investigate the nature and the importance of interactions between industry, academia and government. Companies that are collaborating with universities and research centres perform better in terms of the development of new technologies and products. Companies that are collaborating with other companies (customers, suppliers) perform better in terms of increased turnover from improved products (Faems et al. 2005) or influence labour productivity growth (Belderbos et al. 2004).

Knowledge spillovers play an important role in shaping the regional conditions for innovation activities. Interaction between organisations in regional networks decreases the uncertainty in the innovative process. This kind of interaction is highly dependent on geographical proximity

(Freeman, 1991). Several authors argue that policy could contribute to a wider and faster diffusion of knowledge spillovers by actively stimulating cooperative relationships or motivating to secure a competitive market structure (cf. Jorde and Teece, 1990).

Patent data has been treated as the most important output indicator of innovation for their standardised information relating to new ideas and technological development. Patent data is commonly used in empirical studies to measure innovation performance, knowledge flows and collaborations for its high quality and good availability (Napolitano and Sirilli, 1990; Griliches, 1990/1998; Ahuja, 2000). Since Jaffe et al (1993), patent analyses are particularly appropriate for probing the geographical collaboration relationships for inventive activities. The patent collaboration networks are examined to contribute to policymakers and relevant managers when making decisions for universities, firm localities and choices on collaborators.

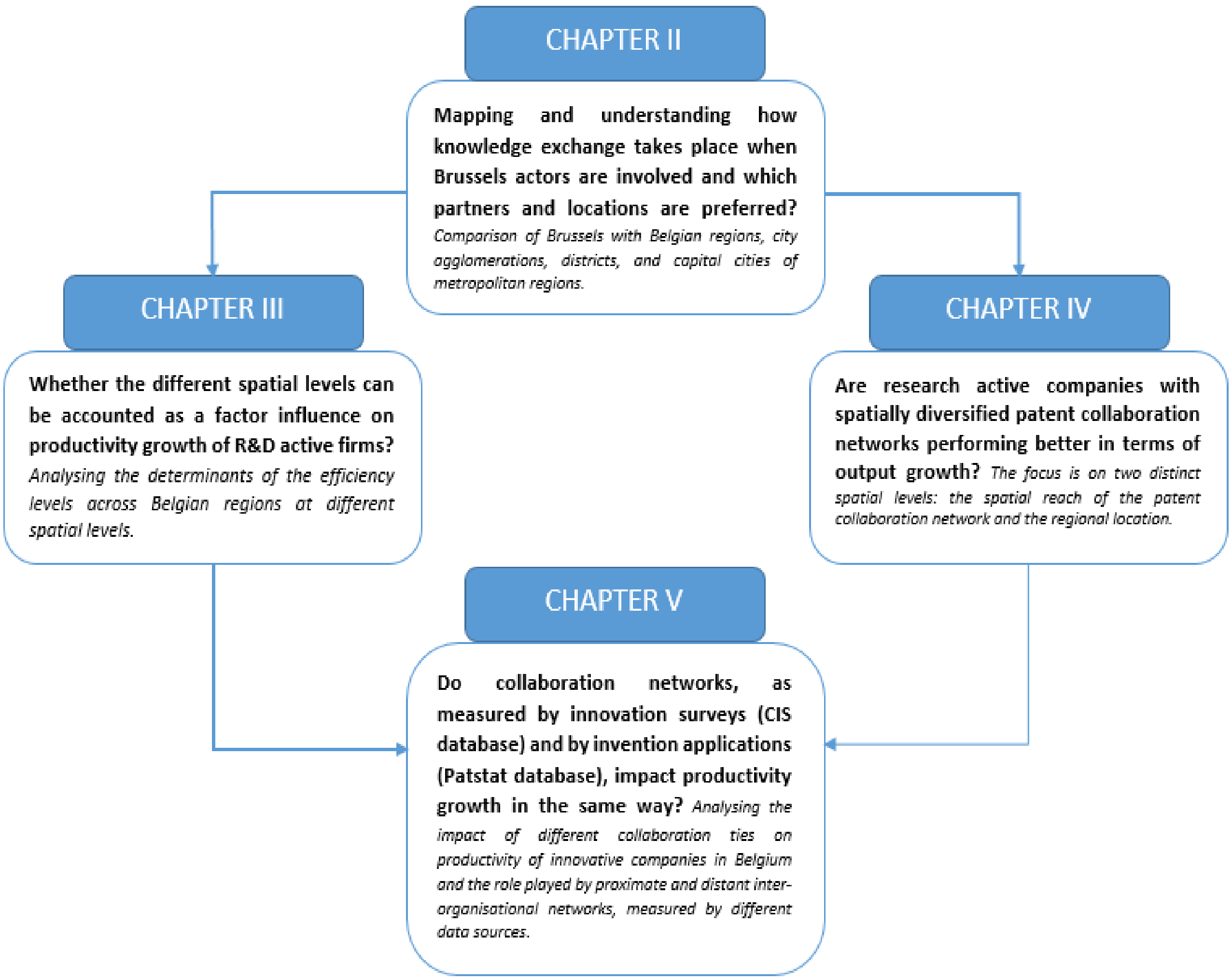
In the following **Chapter IV,** the analysis embraces a wider reach. Although the literature on the relations between patents and output growth of R&D active companies has been widely investigated, there has been little research concerning the impact of patent collaboration networks on the output growth of R&D active companies. In this chapter theoretical developments from the literature are integrated with a conceptual framework that allows us to explain to what extent patent collaboration networks affect output growth. In addition, two distinct spatial levels are covered. First, the spatial reach of the patent collaboration network is considered. Second, the regional location of the company shows differences in patenting activity, patent collaboration, and the spatial reach of the patent collaboration network.

Promoting innovation to stimulate economic growth is one of the main concerns of public policy. There is an increasing need to measure and assess innovations in order to increase the knowledge about the driving forces behind innovations. Nowadays, publicly available, internationally comparable and reliable data on innovation has become accessible. As an example, patent records and innovation surveys data have become relevant indicators of the innovativeness of an economy. R&D expenditure, innovation surveys and patents are three ways to acquire information on the innovative activities of companies. R&D expenditure measures a major input in the innovation process, which is extensively used as proxy for the level of innovative effort. The advantage of this measure is that it is a well understood term and it is measured in a quantitative way (OECD, 2005). Patents comprise innovations that are new and worth to be patented, but at the same time might not be introduced on the market. The last source in terms of innovation indicators is innovation surveys. Innovation surveys usually contain qualitative and quantitative data on innovation activities. They are widely used by scholars and policymakers to observe and monitor innovation performance (OECD, 2005).

Inter-organisational relations are a crucial aspect of knowledge flows, which are at the same time an important engine for innovation. The analysis of **Chapter V** is focused on assessing the impact of different collaboration ties on the productivity of innovative companies in Belgium, measured in several ways through the innovation survey (Community Innovation Survey) and in terms of patents (Patstat). Further, it investigates an alternative spatial approach in order to look into the role played by proximate and distant inter-organisational networks among organisations.

All research objectives are explored individually in the four next chapters of the thesis, which are linked together, as can be seen in the illustration presented in Figure I-1.

**Figure I-1. The link between the chapters of the thesis**



## 1.2 Structure of the thesis

The remainder of the thesis is organised as follows. After Introductory chapter, **Chapter II** presents the benchmarking exercises which is increasingly used as an assessment instrument to guide policymakers. This chapter complements existing information about the Brussels regional innovation system with additional data that is less frequently available through current channels or difficult to make public due to the number of data manipulations. This research illustrates the Brussels innovation system by focusing on various aspects related to intra- and interregional connections. The dataset is based on scientific publications and patents over the period 1993-2013 containing at least one author with an affiliation or inventor located in the Brussels-Capital Region, Vienna and Berlin. The main objective of this chapter is to compare Brussels with Belgian regions, city agglomerations and districts, as well as with capital cities of metropolitan regions (Vienna and Berlin) in terms of patenting and producing scientific publications, in order to map and understand how knowledge exchange takes place when Brussels actors are involved and which partners, locations, scientific fields and technological sectors are preferred.

**Chapter III** deals with the topic of the spatial pattern in R&D activities. It is worthwhile to explore the dynamism and change of R&D activities' spatial spread as R&D activities are very much a dynamic phenomenon and the consequences in terms of past growth have painted the current relative position of the regions. In this chapter we analyse the determinants of the efficiency levels across Belgian regions at different spatial levels (3 regions, 10 provinces, 43 districts, and city agglomerations), we derive a regression based on the measurement of regional output growth by estimating an extended Cobb-Douglas production function bases on a representative sample of Belgian R&D active firms over the period 2000-2010. We investigate the role played by knowledge (private and public R&D stocks) on the output growth by applying the spatial econometric methods. The paper focuses on the comparison of obtained results with previous research works have been produced for Belgium.

In **Chapter IV** we continuing our analysis based on the methodology and some ideas of Chapter III, where we primarily concerned with the following research question: are research active companies with spatially diversified patent collaboration networks performing better in terms of output growth? This Chapter extends the existing literature in several ways. First, we focus on identifying all possible co-application relations among patent applications in Belgium, giving a view on a more detailed country profile in terms of patent co-application ties. Second, we analyse the impact of a particular co-application tie among patent applications (company-individual) on output growth of R&D active companies in Belgium. This Chapter uses a novel spatial approach to look into the role played by proximate and distant patent collaboration networks among inventors involved in company-individual co-application relations. The spatial reach of the network, therefore, becomes a central topic of Chapter IV. The spatial reach is decomposed into three categories (BE, EU and ROW) allowing for existing overlaps. This enables an identification of a combination of patent collaboration network locations driving output growth. Finally, we test regional differences in order to see the willingness of companies and individuals to cooperate on patents and to demonstrate their impact on the spatial reach of the patent collaboration network.

**Chapter V** explores the impact of different collaboration ties on the productivity of innovative companies in Belgium, measured in several ways through the innovation survey (Community Innovation Survey) and in terms of patents (Patstat). Inter-organisational relations are a crucial aspect of knowledge flows, which are at the same time an important engine for innovation. Collaboration has become an ever more important feature of entrepreneurial strategy to innovate. Network ties facilitate companies' innovative capabilities by acting as key sources for innovations, helping to access the resources and boosting knowledge transfer. Chapter V extends the existing literature in several ways. First, we analyse the impact of different (measurements of) collaboration ties on productivity of innovative companies in Belgium. Second, we use an alternative spatial approach to look into the role played by proximate and distant inter-organisational networks, measured by different data sources, which in turn broaden the scope and enrich our understanding of collaboration ties.

Main results, limitations of research, policy implications, final remarks and avenues for further research are presented in **Chapter VI**.

## CHAPTER II

# MAPPING SCIENCE AND TECHNOLOGY KNOWLEDGE STOCK AND FLOWS IN THE BRUSSELS-CAPITAL REGION

This chapter is based on the INNOVIRIS project "Prospective research for Brussels 2014", "Brussels knowledge flows: localised learning and regional knowledge pipelines (BLOCPIPE)", ULB, Belgium.
First version of the paper was presented at the Master and Doctoral Consortium for Research on Public Policy (Universidade de Evora, Evora, Portugal, June 2016) and updated version of this Chapter was presented at 11th Regional Innovation Policies Conference (RIP) (Cardiff, UK, November 2016).

## SUMMARY

*Benchmarking exercises are increasingly used as an assessment instrument to guide policy-makers. They contribute to policy-making in three broad ways: delineating and monitoring development and progress; facilitating the exchange and gathering of knowledge on practices and policies; and promoting the image and attractiveness of economies. This research complements existing information about the Brussels Regional Innovation System (BRIS) with additional data that is less frequently available through current channels or difficult to make public due to the number of data manipulations. This research illustrates the Brussels innovation system by focusing on various aspects related to intra- and interregional connections. The dataset is based on scientific publications and patents over the period 1993-2013 containing at least one author with an affiliation or one inventor located in the Brussels-Capital Region, Vienna and Berlin. Patents and scientific publications provide a clear picture of the nature of technological change and innovation. Moreover, these sources give some further indication of R&D activities in the field and the position and specialisation of countries. The main benefit of such indicators is the unique empirical characterization they provide of the way actors interact as a collective system of knowledge production and diffusion (OECD, 1996). The main objective of this work is to compare Brussels with Belgian regions, city agglomerations and districts, as well as with capital cities of metropolitan regions (Vienna and Berlin) in terms of patenting and producing scientific publications, in order to map and understand how knowledge exchange takes place when Brussels actors are involved and which partners, locations, scientific fields and technological sectors are preferred. The main focus is on providing basic information about patent and scientific publication data, the construction of indicators based on patents and scientific publications, as well as guidelines for the compilation and interpretation of patent and scientific publication indicators.*



***Keywords:*** *Benchmarking exercises, metropolitan areas, Brussels, Berlin, Vienna, Scopus, PATSTAT, innovation policy.*

***JEL codes:*** *C8, O10, O30, O34, R12*

## 2.1 Introduction

“Buyers, sellers, administrators, streets, bridges, and buildings are always changing, so that a city’s coherence is somehow imposed on a perpetual flux of people and structures. Like the standing wave in front of a rock in a fast-moving stream, a city is a pattern in time. “(Holland, 1995).

The main focus of policy makers is to capture regional specificities and inter-regional linkages in order to support regional economic development. The role of cities in countries’ and regions’ economic and social performance has increased policy-makers’ awareness of metropolitan areas as strategic places (Brezzi et al., 2012; Cincera et al., 2012). Regions show significant differences which can be assessed regarding their R&D infrastructure, different patterns of technological specialisation and the “openness” of their innovation systems (OECD 2013). In addition, metropolitan regions are increasingly seen as regional development engines in a globalizing world (Huggins, 1997). There are two main aspects which play an important role in innovations: first of all, metropolitan regions are able to facilitate agglomeration economies in the form of urbanization and localisation economies for their actors, and secondly, they function as gateways for other regions, thereby linking local actors with national or international ones (Diez, 2002). Today, central locations are very convenient for administrative functions with a large sedentary workforce since they are usually served by a dense net of mass public transport (Van Criekingen et al., 2007).

Metropolitan cities are characterized by a high degree of openness. Almost half the population of OECD countries live in metropolitan areas, contributing more than 50 % of OECD GDP and accounting for 60% of patents in the OECD area (OECD Regions at a Glance, 2013). R&D and patenting are most concentrated in the top regions of knowledge-intensive OECD member countries, and those regions have different technology paradigms (green technologies, biotechnology and ICT, for example) (Regions and innovation policy, OECD, 2011).

In this study we are positioning the Brussels-Capital Region in relation to other regions/metropolitan regions and other spatial levels (OECD 2013). It complements existing information about the Brussels regional innovation system with additional data less frequently available through current channels or difficult to make public due to the number of data manipulations. This research illustrates the Brussels innovation system by focusing on various aspects related to intra- and interregional connections.

The Brussels-Capital Region is not on track to reach its research and development (R&D) intensity target of spending 3% of its gross regional product on R&D by 2020. Total R&D intensity reached 1.16% in 2003, in 2009 it was 1.53% and stabilized at 1.51% in 2013 (Eurostat, 2016). However, the innovation system is not only about performance in terms of R&D but is much more than that. This study places R&D performance next to other relevant indicators such as scientific publications and patents. These indicators are all influenced by, and will simultaneously influence, the Brussels innovation system.

The main objective of this work is to compare Brussels with Belgian regions, city agglomerations and districts, as well as with capital cities of metropolitan regions (i.e. Vienna and Berlin) in terms of patenting and production of scientific publications, in order to map and understand how knowledge exchanges take place when Brussels actors are involved and which partners and locations are preferred. Patents and scientific publications provide a clear picture of the nature of technological change and innovation. Moreover, these sources allow some further indication of R&D activities in the field and the position and specialisation of countries. The main benefit of such indicators is the unique empirical characterization they provide of the way actors interact as a collective system of knowledge production and diffusion (OECD, 1996). The main focus is on providing basic information about patent and scientific publication data, the construction of indicators based on patents and scientific publications, as well as guidelines for the compilation and interpretation of patent and scientific publication indicators.

This chapter is organised as follows. Section 2.2 briefly discusses regional innovation policy. A systematic review on the topics of regional and agglomeration city benchmarking is outlined in Section 2.3. Section 2.4 introduces the main stylized facts about Brussels, Berlin, Vienna and their hinterlands. Section 2.5 provides the data-gathering process, methodology and summary for the patent indicators. Section 2.6 deals with the data-gathering process, methodology and a summary of the scientific publication indicators. Section 2.7 provides SWOT analysis followed by geographical illustrations in Section 2.9. A few final remarks and some prospects for possible further research are presented in Section 2.9.

## 2.2 Knowledge flows: local buzz and global pipelines[1]

At the policy level, the Brussels Capital Region aims to become a knowledge-based region. However, it should be acknowledged that very few regions are self-sufficient when it comes to possessing an adequate knowledge base. Moreover, the existence of increasingly complex technologies forces organisations to turn to a variation of network relations to gather the components needed for innovation and economic growth (Kash and Rycroft, 2000). Not all these components and partners may be present within the region. Hence, an innovation system requires knowledge flows that continuously offer inputs (local/regional or global).

The main idea in the work of Bathelt et al. (2004) is that successful innovation systems are characterised by actors that succeed in establishing and coordinating many channels through which they can access relevant knowledge from wherever it is located. They posit that the skill to use local knowledge differs from the skill to handle global knowledge. In order to be successful, actors in the innovation system should include both skills.

Local knowledge belongs to a ‘local buzz’ that incorporates all local knowledge flows (Storper and Venables, 2004). Local buzz ensures that knowledge circulates in the region, whether formal or informal, tacit or codified, intentional or unintentional, individual or co-ordinated. The common element is that the knowledge is transmitted because of the co-location, and the local buzz operates as the oil in the network.

[1] This is joint work carried out within the Innoviris and BRUSTI project.

Global knowledge pipelines refer to distant interactions with a network of knowledge creating actors and are co-dependent on the strength of the network relations, the level of trust in the relationships, etc. The knowledge obtained from global pipelines gives local actors the advantage to tap into the most effective technologies or the latest scientific insights that help them to reinforce their competitiveness and innovative capacities.

Most actors in the innovation system will require both local buzz and global pipelines to be successful, only on the assumption that they have sufficient internal absorptive capacity to recognise, assimilate and exploit this knowledge.

In spite of the abundance of science and technology indicators, there is little evidence produced on local buzz and global pipelines. This study presents two indicators that highlight these dimensions of knowledge flows using available information in a novel way.

### 2.2.1 Regional innovation policy[2]

Regional innovation policy should be seen as operating in the framework of mainstream public policy. To this end, its goals and targets have to be in line with adjacent policy domains such as industrial policy directed to specific sectors, spatial policy providing infrastructure, mobility policy to enhance accessibility of economic agents, etc.

The reason for innovation policy to step into the political arena is to remedy market failures decreasing the return on private R&D investments, system failures hindering the free flow of knowledge and technology and the existence of lock-in and path dependency. Knowledge spillovers, irrespective of their form of appearance or channel characteristics, all have a certain geographical 'reach' with implications for industrial managers, university administrations and policy makers. Industrial leaders are attracted by the available knowledge base to tap into it and use the insights to develop new saleable applications. University administrators are currently also looking for interesting industrial partners to complement their research budgets; and are increasingly important players in regional economic development by indirectly constituting the knowledge base and directly by their actions as entrepreneurial universities through spin-off and patent activity. Policy-makers, especially in times of strict budget guidelines, must be aware of the geographical reach of knowledge spillovers to be able to devise a policy that contributes to those factors that strengthen the attractiveness of the region without stimulating activities that might be tempted to 'leak out' of the region.

The region makes use of regional innovation plans to implement its innovation strategy. In its most recent version, a smart specialisation approach has been favoured. The idea is to identify desirable areas for innovation policy intervention favouring certain technologies and types of companies. Although the logic of the benefits of specialisation remains intact, smart specialisation acknowledges that, for small regional economies in Europe where it is difficult to identify what should be prioritised, an adapted policy method is needed. Foray and van Ark (2007) stress that the smart specialisation strategy is not without its problems as it currently lacks transparency,

[2] This is joint work carried out within the Innoviris and BRUSTI project.

verifiability and consensus. They posit that many statements and arguments about smart specialisation are not yet based on sound empirical foundations. This runs the risk of smart specialisation being misused to reflect ad hoc ambitions or opportunistic pleas, rather than a robust and defensible strategic case for action. To help policy-makers in their reflections on smart specialisation there is a need for additional science and technology indicators such as those in this study in order to capture the interrelatedness of the Brussels-Capital Region with other regions and knowledge hubs as well as the scientific fields and technological sectors where the Brussels-Capital Region has clear comparative advantages.

The Brussels-Capital Region must take the multi-level character of innovation policies into account by acknowledging there are significant variations among regions according to legislative and budgetary powers, which leads to different policies, institutions and regional co-ordination mechanisms. To stimulate R&D activities, attract innovative firms, enhance knowledge production through scientific publications and commercialise technology using patents, regions are in fierce competition for critical resources, such as human resources, and offer favourable framework conditions. Therefore, given the close interrelation between innovative performance and economic competitiveness, innovation policies are faced with the problem of tension between market co-ordination and political co-ordination.

Innovation policies are still developed within national or regional administrative boundaries, while capital, labour and knowledge flows occur more and more at an international and global level. However, not all the problems a region faces can be solved at the regional level, nor are all problems due to internal structural causes (OECD, 2011).

## 2.3 Brussels: region and agglomeration[3]

The focus of innovation systems is to generate, distribute and use knowledge, while all these activities face a problem with the concept of geographical boundaries. Moreover, a strongly debated issue is the meaning of administrative boundaries for innovation policy.

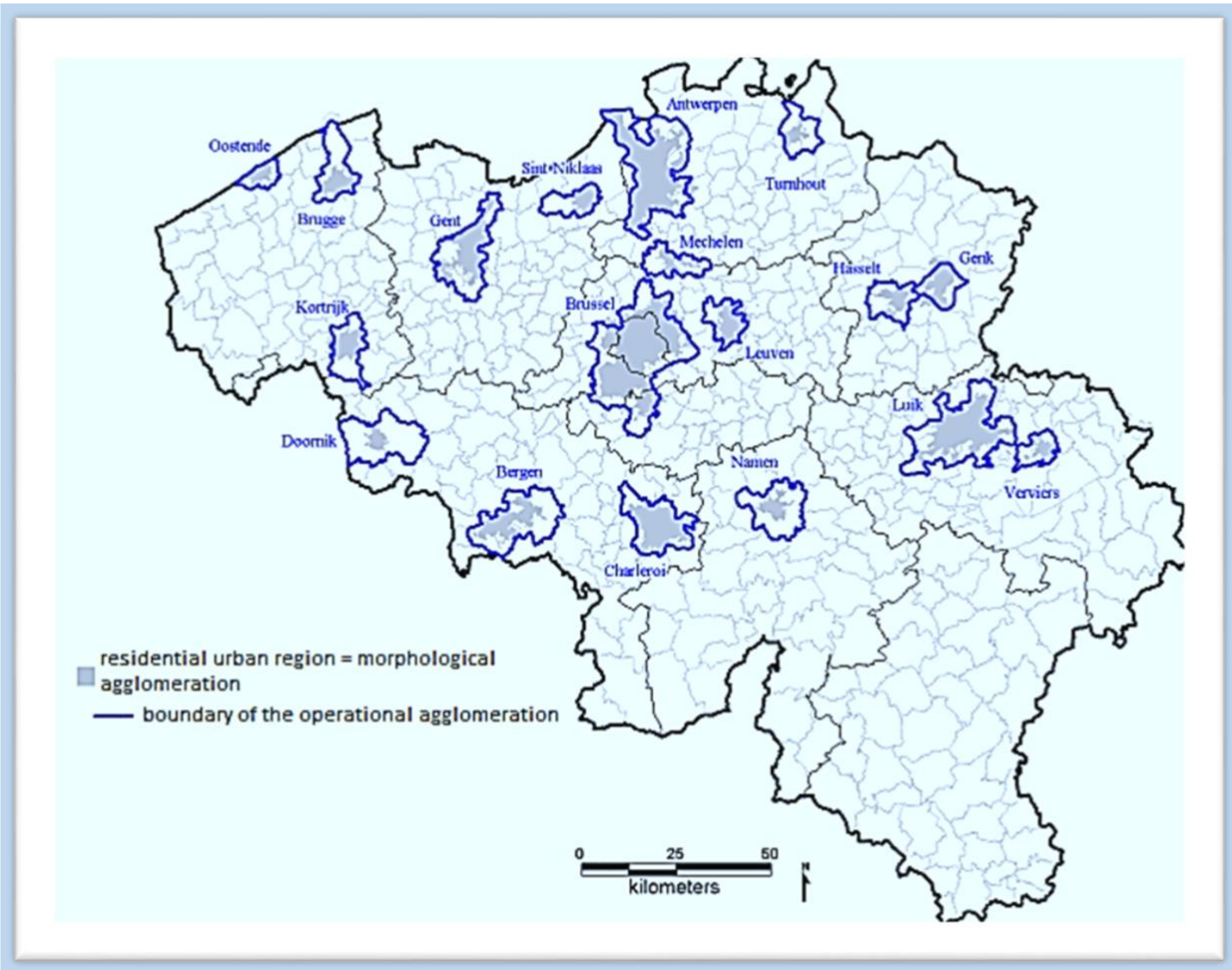
Moulart and Sekia (2003) indicate that innovation systems are usually analysed in the context of administrative regions: national, regional, metropolitan or local. The main reason for this is that innovation systems are much used in policy-related texts (OECD, 1995, 2005). When analysed as functional regions, large cities inevitably come to the fore as ‘regional innovation systems’ forming an environment based on interactive linkages between different types of actors located in the same area (Cooke et al., 1997; Iammarino, 2005). However, the resource-based view predicts that when firms are sourcing new knowledge and technology, they will aim to acquire it irrespective of its location (Spithoven & Teirlinck, 2015), whether enhanced by institutional, cognitive or social proximity (Boschma, 2005). Therefore, innovation in regions cannot be seen in isolation from the regions’ hinterland and there is a need to capture the morphological territory of the city region, denoting an urban zone with multiple administrative districts, sharing resources

[3] This is joint work carried out within the Innoviris and BRUSTI project.

such as a central business district, labour market and transport network, so that it functions as a homogeneous unit.

Besides the classical divide between the Brussels-Capital Region, the Flemish Region, and the Walloon Region, this study uses the operationalisation of city-regions based on many different socio-economic and spatial indicators from the most recent census of 2001 (Luyten & Van Hecke, 2007). Figure II-1 is restricted to the agglomeration of 18 city-regions based on morphological agglomeration but making use of the boundaries of the municipalities in which they lie.

**Figure II-1. Region and agglomeration**




Source: Charlier J., Van Hecke E., Luyten S. SEGEFA-ULg, ISED-KULeuven, 2006

Note: See Luyten, S., Van Hecke E., (2006) Instituut voor Sociale en Economische Geografie, K.U.Leuven Working paper "De belgische stadsgewesten 2001" - https://statbel.fgov.be

In total, there are three categories of city-regions that are relevant in this study when comparing the Brussels city agglomeration to other agglomeration types. Brussels city agglomeration is a special case as Brussels hosts many international organisations (NATO, EU), headquarters of multinational companies, and many higher education institutions (universities, university colleges and university hospitals). A second category consists of four large city agglomerations (Antwerp, Liege, Gent and Charleroi). The third category is made up of 13 regional city agglomerations

(Brugge, Genk, Hasselt, Kortrijk, Leuven, Mechelen, Mons, Namur, Oostende, Sint-Niklaas, Tournai, Turnhout and Verviers).

### 2.3.1 City benchmarking: Brussels, Berlin and Vienna

Benchmarking exercises, initially developed to compare firm performance, have been progressively transferred and applied also to the territorial context, first to national governments, then to European Union policies and to regions (Koellreuter, 2002). In recent years they have become increasingly popular for policy makers. Some researchers state that regional benchmarking is an essential prerequisite for informed and strategic policy making, which provides a way for cities and regions to learn which local strengths are being assembled elsewhere. (Martin, 2005; Rota & Vanolo, 2006; Malecki, 2007). Benchmarking is a method of `learning by comparing' (Huggins, 2010; Boxwell, 1994). Critical analysis of the benchmarking exercise has questioned to what extent benchmarking efforts are consistent with endogenous approaches to regional development, and the importance of measuring and understanding factors such as human capital, education, production and innovation systems from a regionally external perspective to support such development (Moulaert & Sekia, 2003). It is now acknowledged that regional economic development, competitiveness and innovation policies form part of the institutional architecture through which regions ‘learn’ (Asheim, 1996; Morgan, 1997).

The work of Lurcovich et al. (2006) highlights that regional performance relies on political, economic and social factors beyond the control of a single authority. As a result, regional benchmarking differs considerably from firm benchmarking. It is easier to compare data at the scale of countries rather than regions or cities. That is why benchmarking exercises have the potential to form part of the toolbox of instruments available to regional policy makers (Huggins & Izushi, 2009). The benchmarking exercise contributes in three broad ways: delineating and monitoring regional economic development and its progress; facilitating the exchange and gathering of knowledge about regional practices and policies; and promoting the image and attractiveness of regional economies (Huggins, 2009). Regional benchmarking is progressing in its development through time. Creating a benchmark exercise at a city level requires identifying sources of common information about the city’s value elements. The most common way to do this is to use international rankings, which is a relevant option as it evaluates cities with a specific and public methodology. To analyse and improve a city’s performance, measurement information must be produced to capture the status of relevant variables (Yigitcanlar & Lönnqvist, 2013). The OECD has developed different standardized approaches for science and technology indicators, as well as the use of simple aggregated rank tables of countries' innovation performance (Grupp & Mogee, 2004).

Choosing the cities of metropolitan regions for comparison is the first step of any regional benchmarking exercise. City benchmarking enables us to make a comparative identification of those key elements that will help guide future lines of strategy to be implemented, as well as serving as the basis for evaluating the results. For that reason, Berlin and Vienna have been selected as a basis to compare the trends and performance of the indicators between Brussels and other cities. Comparing Brussels with Vienna and Berlin is particularly relevant, because of several important institutional and geographical similarities as well as comparable innovation systems. Navarro et al. (2014) developed a methodology to identify regions that share similar structural conditions which are relevant for innovation-driven development (social, economic, technological, institutional and geographical characteristics). Based on regional data for European Union Member states, a matrix of inter-regional distances was constructed by these authors and used to analyse the design and implementation of smart specialisation strategies. According to this matrix the distance indexes between the Brussels-Capital Region, Berlin and Vienna are the smallest. Table II-1 presents key economic indicators for these three capital cities of metropolitan regions for 2016.

**Table II-1. Main indicators for capital cities of metropolitan regions, 2016**

| | Population | Education level, Bachelor | Employment (people aged 15–64) | GDP (1) |
|---|---|---|---|---|
| | million inhabitants | thousands | Thousands | million EUR |
| Brussels | 1.2 | 87(1) | 440 | 75 |
| Vienna | 1.8 | 103 | 815 | 87 |
| Berlin | 3.5 | 104 | 1698 | 124 |

(1)2015
Source: Eurostat, online database.

## 2.4 Stylised facts

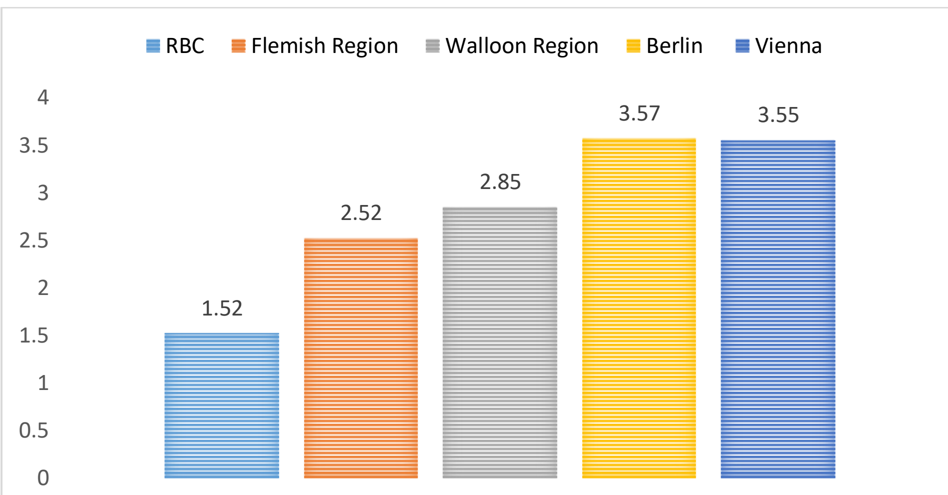
Metropolitan regions are increasingly seen as regional development engines in a globalizing world (Huggins, 1997). They are characterized by a high degree of openness and linked to cooperation partners worldwide. A comparison between the metropolitan regions of Brussels-Capital, Berlin and Vienna is provided in this section aiming to shed some light on some general facts about these regions.

The Brussels-Capital Region, created in 1989, is characterised as a multilingual, high-quality research system with a high gross regional product and hosting many international, national and regional representative agencies and organisations. Being the capital of Europe but also centrally located geographically speaking, the city attracts a great number of international companies. The Brussels-Capital region remains an essential link in the chain of activities of the chemical sector in the country. This region has only a few chemical production facilities but attracts various head offices, such as those of BASF and Statoil, which are near to several international organisations and institutions. Brussels is a clearly preferred location for the establishment of coordination centres, although there are some in other parts of the country (De Beule & Van Den Bulcke, 2010). Brussels is the most important Belgian region in terms of economic activities and investment incentives. The R&D system is to a large extent oriented towards product innovation. The region contains 19 autonomous municipalities, referred to as the city of Brussels. Universities are distributed all over the country, but 8 university institutions are in the Brussels-Capital Region and its hinterland (the Flemish and Walloon part of the Brabant province).

Berlin is a serious player in the group of global cities, functioning as an "international node within the world's network of growth sectors" (Kratke, 2001). Berlin is the largest city in Germany with 3.5 million inhabitants. Over the last decade, the city has been at the centre of dramatic changes and has been forced to change itself from a global perspective (politico-economic positioning). Regarding R&D productivity, Berlin is characterised more as a centre of cultural production than a centre for R&D-intensive industries (Kratke, 2000).

Vienna is the administrative centre of Austria and it has also a long tradition as one of the major locations for science and research. The city has a population of 1.8 million inhabitants. In the metropolitan area the population is about 2.6 million people. Vienna is also a major centre of economic activity, including some manufacturing industries (Kaufmann, 2007). The most important are electronics, electrical equipment, food and beverages and printing (Wien Statistik 2002). The metropolitan system of Vienna pursues innovativeness, but the weak contribution of the private business sector to the metropolitan innovation system is noted, as expressed in low business expenditure on R&D (Diez, 2002).

**Figure II-2. Gross domestic expenditure on R&D (% of GDP), 2013**




Sources: Eurostat, PPS Science Policy, National Accounts Institute, IBSA and Innoviris calculations

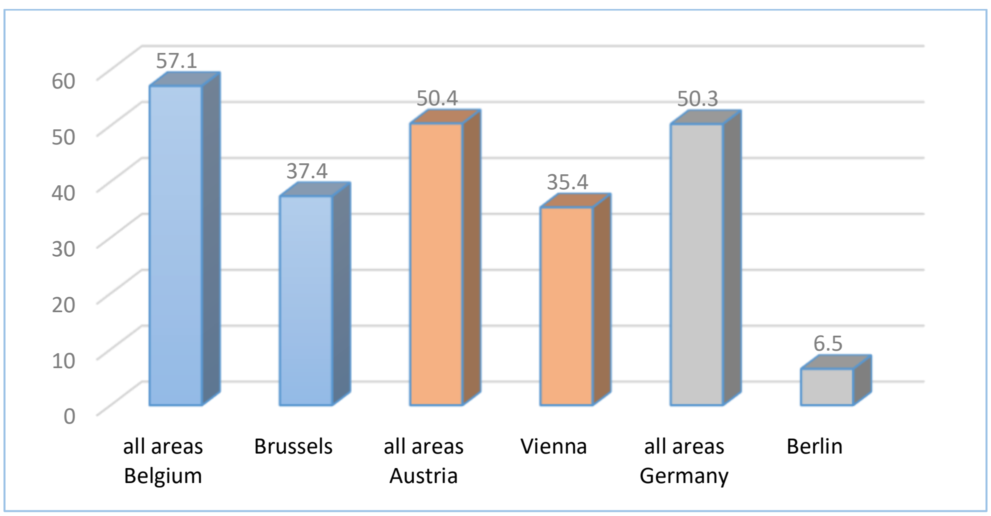
Analysis of the three metropolitan regions, Brussels-Capital, Berlin and Vienna, provides interesting insights into the innovative activity within regional innovation systems (see Figure II-2). Brussels R&D intensity lies below the European and Belgian average. In 2013, it was 1.52% against more than 2% on average in EU-28 (2.52% and 2.85% in Flanders and Wallonia respectively). The other European capitals show higher results (Kalenga-Mpala & Wautelet, 2016[4]). As explained in the work of Vaesen et al., (2014), relatively low levels of R&D in Brussels-Capital region (particularly in companies) can be explained by the comparative weakness of high

[4] http://statistics.brussels/files/publications/focus-de-libsa/FOCUS-12-FR-final.pdf

and medium-high technology sectors where the level of R&D intensity is typically high, such as the pharmaceutical or electronic industry. This deficit is understandable as Brussels is an international city focused on administrative functions. Since 2004, the Brussels authorities have acknowledged the potential contribution of research and innovation to economic development and launched their regional strategic plan to support these activities. The first regional innovation plan in 2005 proposed an increasing budgetary share for research and innovation. Overall the strategy is targeted at three innovative sectors – ICT, health and the environment – which are identified as the most promising ones and justifying the allocation of more public resources to stimulate them.

According to Figure II-3 and Figure II-4, metropolitan areas in Belgium concentrate 52% of national GDP and 44% of employment. During 2000-2010, Belgian areas accounted for 57% of GDP growth, while Austrian areas concentrated 51% of national GDP and 46% of employment. In the period of 2000-2010 Austrian areas accounted for 50% of GDP growth. Metropolitan areas in Germany concentrate 44% of national GDP and 39% of employment, accounting for 50% of GDP growth, as compared to the OECD average of 60%. Belgium had the 5th largest regional disparity[5] in GDP per capita[6] in OECD countries in 2010. GDP growth between Belgian regions indicates similar trends for the period 2000-2010, e.g. between + 1.5% per year for Wallonia and + 1.4% in the Flemish region (Panorama des régions de l'OCDE, 2013). Austria has the second lowest regional disparity in GDP per capita in OECD countries. In the past decade, GDP growth in the Austrian regions was above the OECD average, with the largest difference observed between Vorarlberg (+1.9% annually) and Carinthia (+1.2% annually) (OECD Regions at a Glance, 2013). Germany had the 7th largest regional disparity in GDP per capita in OECD countries in 2010. In the past decade regional growth ranged from +1.6% annually in Hamburg to +0.1% in Schleswig-Holstein (OECD Regions at a Glance, 2013).

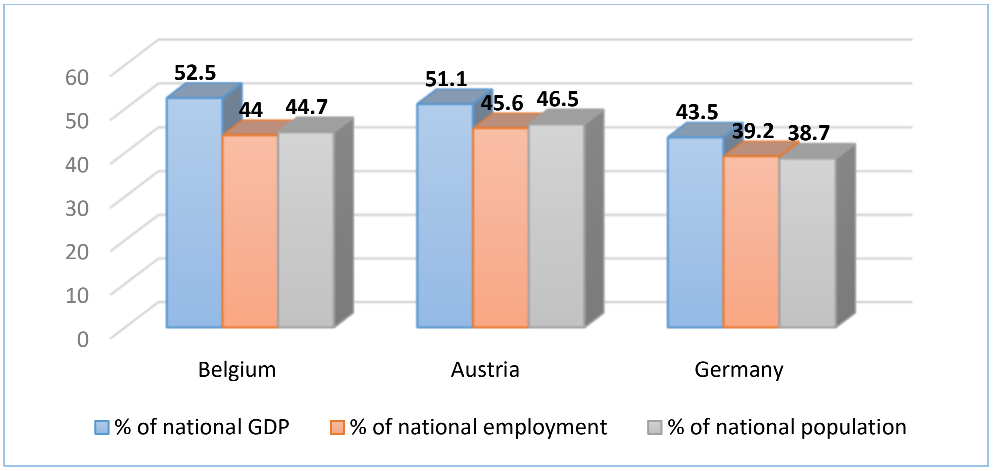
**Figure II-3. Metropolitan areas' contribution to national GDP growth, 2000-2010**




[5]Regional disparity means unbalanced spatial structures in some region or in different regions. Large differences persist in the contribution of regions to the national wealth and economic competitiveness.
[6] GDP per capita is calculated by dividing the GDP of a country or a region – measured at constant Purchasing Power Parity (PPP) (2000) – by its population.

Sources: OECD

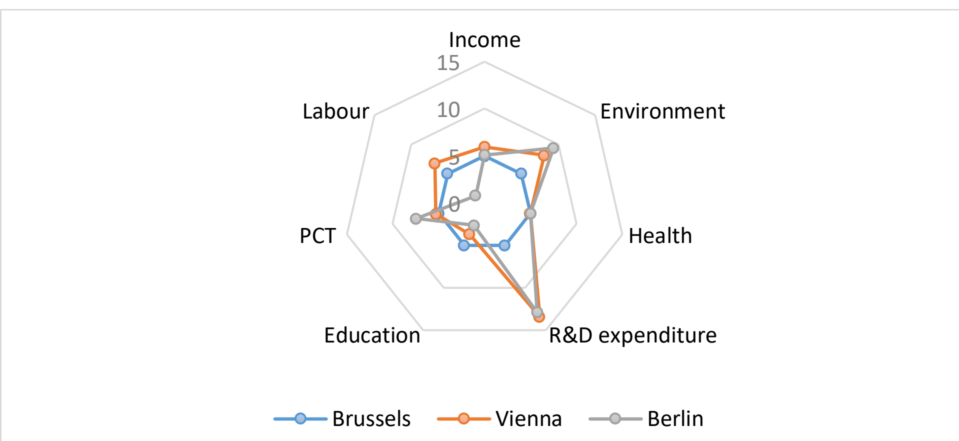
**Figure II-4. Concentration in metropolitan areas, 2010**




Sources: OECD

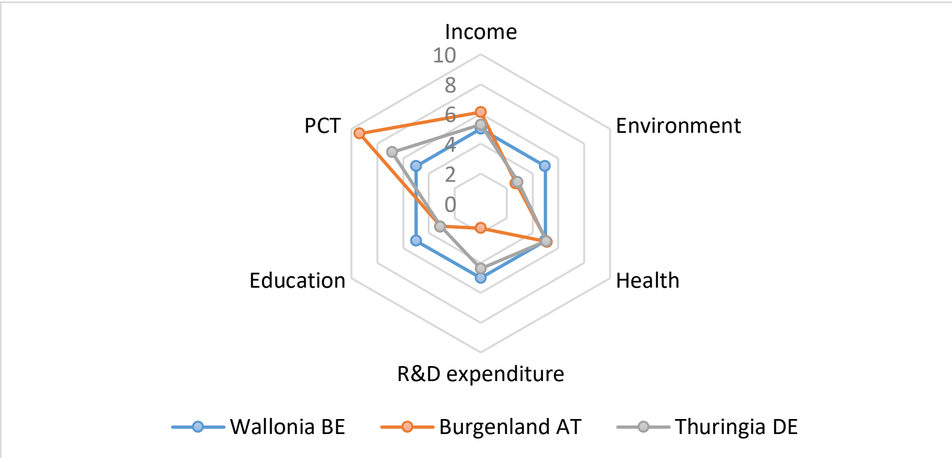
Figure II-5 illustrates the performance of three metropolitan regions with the highest GDP per capita in terms of social and environmental dimensions. The Brussels-Capital region is considered as a median to make a reliable comparison with other regions. Based on the results, the Brussels-Capital Region performs better only in the Education sector, whilst the other sectors indicate higher values in Vienna and Berlin regions. In R&D expenditure, Berlin and Vienna show slightly different outcomes. In the Health sector, the indicator reveals the same distribution with a slight difference between regions. Berlin shows a rather poor performance in the Labour sector compared to Brussels-Capital and Vienna regions. Regarding the Income indicator, we observe barely different results in all metropolitan regions.

**Figure II-5. Comparison of BCR with Vienna and Berlin regions (with the highest GDP per capita) in social and environmental dimensions**




Sources: OECD, own calculations, last available year
R&D expenditure - R&D expenditure Total as %of GDP
PCT - PCT patent application per million inhabitants
Labour - Labour force of the metropolitan area as a share of national value%
Income – Regional income per capita
Brussels is a median region equal 5. The more the radar graph is covered, the better the performance of the region compared with Brussels-Capital region (BCR). Data for the last available year.

**Figure II-6. Comparison of Wallonia region with Burgenland and Thuringia regions (with the lowest GDP per capita) in social and environmental dimensions**




Sources: OECD, own calculations, last available year
R&D expenditure - R&D expenditure Total as %of GDP
PCT - PCT patent application per million inhabitants
Labour - Labour force of the metropolitan area as a share of national value%
Income – Regional income per capita
Wallonia is a median region equal 5. The more the radar graph is covered, the better the performance of the region compared with Walloon region). Data for the last available year.

Looking at the regions with the lowest GDP per capita, Belgium is represented by the Walloon region, Germany by Thuringia region and Austria by the Burgenland region (see Figure II-6). The methodology used to construct these indicators is based on the previous indicator with the highest GDP per capita (see Figure II-5). The results show that the Walloon region performs more successfully than the other two regions. Only in the PCT sector do Thuringia and Burgenland show higher performance. We observe slightly different performance in the regions in the Income indicator, where Wallonia presents the lowest value. In R&D expenditure Wallonia performs better than Thuringia and Burgenland.

Analysis of the three metropolitan regions, Brussels-Capital, Berlin and Vienna, provides interesting insights into the different activities within regional innovation systems. Across the three metropolitan cities, similarities and differences are visible.

## 2.5 Patent output: key features and trends

A patent is an intellectual property right that gives its owner the exclusive right to use their invention in a particular technical field for a limited number of years (in general 20 years). As is well known, patent data can be analysed in a variety of ways to fulfil different purposes. Patent analysis is also a valuable approach that uses patent data to derive information about an industry or technology. Today patents can be used to understand the past and even potentially to forecast the future. Patent-based indicators help to explore, organise and analyse large amounts of data, identifying “hidden patterns” that may help policy analysts in the decision-making process. Patents are of interest to economists, industrialists and policy makers for three main reasons: they help stimulate investment in innovation, they contribute to monopoly power, and they are a rich source of qualitative and quantitative information on technological change (Kürtössy, 2004).

The aim of this section is to provide basic information about patent data, the construction of indicators[7] based on patents, and guidelines for the compilation and interpretation of patent indicators.

### 2.5.1 PATSTAT database and comparison of Brussels at city, regional and international levels

Patent data provide elements to measure the results of resources invested in R&D activities, and trends in technical change over time. In this study, we use the PATSTAT database which is the main source of gathering information on patents.[8] PATSTAT contains bibliographical information and the legal status of patent documents granted in more than 100 patent offices worldwide, starting from the nineteenth century. The information contained in PATSTAT is presented through a set of tables that follow a relational database structure where tables can be differently connected to each other to obtain the necessary information by using relevant entry keys. The tables in the PATSTAT database contain information on all patent applications, e.g., inventors and owners, technology fields, titles and abstracts, publication dates and citations, names, addresses, countries of inventors.

The data used in this chapter are based on patents applied at the European Patent Office (EPO) or US Patent and Trademark Office (USPTO) over the period 1993-1994 to 2013 with at least one inventor located in Brussels, Berlin or Vienna. Berlin and Vienna have been selected as a basis to compare the trends and performance of the constructed patent-based indicators.[9] In fact, four levels of spatial aggregation are considered to compare the patent-based indicators: the regional level (Brussels-Capital, Flanders and Wallonia), the metropolitan and regional city agglomeration levels[10] and the international level (Brussels, Berlin and Vienna).

### 2.5.2 Methodology

A patent document contains the following information: the title, abstract and full description of the invention, the year of invention (priority year), the name, address and nationality of the owner of the invention, the technological classes to which the patent belongs, references to both the relevant scientific literature and previous patents, etc. (see PATSTAT Biblio). A patent application should be based on a new solution to a technical problem which satisfies three criteria: novelty;

[7] An indicator is a quantitative or a qualitative measure derived from a series of observed facts that can reveal relative positions (e.g. of a country) in a given area (Nardo et al., 2005).
[8] We used the 14.24 PATSTAT Biblio (raw data) edition 2016 - Autumn of the database and rely on the MySQL relational database management system to process the information in PATSTAT.
[9] See Section 3.
[10] For the metropolitan city agglomeration level, we consider Antwerp, Liège, Gent and Charleroi while for the regional city agglomeration level we take into account Brugge, Genk, Hasselt, Kortrijk, Leuven, Mechelen, Mons, Namur, Oostende, Sint-Niklaas, Tournai, Turnhout and Verviers.

inventiveness; and industrial applicability. A patent may be granted to an enterprise, a public body, or an individual (OECD Patent Statistics Manual, 2009).

As well known, patents represent one of the most important indicators to study the impact of inventiveness on the economic environment and to trace interactions and technology flows across sectors, countries, cities and firms. Patent-based indicators provide a measure of the output of a country's R&D. Patents give unique information on the technical fields of inventions and can also reflect inventors' type of output or their mobility and networks. Patents allow tracking the diffusion of knowledge such as the influence of one invention on another.

Hall (2004) concluded that patents as indicators can be useful and important, especially citation-weighted –correlated with value, R&D, litigation, profits, etc. Nevertheless, it is important over time to understand the impact of policy changes on these indicators (Hall, 2004).

When compiling or analysing indicators with patents attributed to spatial levels (in our case region, districts, city agglomeration), it is important to follow some rules in order not to misinterpret the indicators. The first rule is to remember that the inventor's address indicates where the invention was made, however the owner's address indicates where the holder has its headquarters. The second rule is to specify if inventors in two regions can be attributed wholly to the two regions, or shared (with a total share of 100%) between the two regions/provinces/cities. And the last one, the priority year is the year of first filing for a patent; it is the closest to the actual date of invention and should therefore be used as the reference date when compiling patent indicators (van Pottelsberghe et al., 2001).

Patent data provide a rich source of information on various aspects of innovation activities and they are also available as long-time series. However, they have some advantages and limitations.

Advantages:

- Closely linked to inventions
- Covering a broad range of technologies on which there are sometimes few other data sources available
- Patent data is a rich source of information
- Availability of patent data as long-time series and across many countries

Limitations:

- The value distribution of patents is skewed as many patents have no industrial application whereas a few are of substantial economic value
- Many inventions are not patented because they are not patentable, or inventors may protect their inventions using other means, for example industrial secrecy on lead time
- The propensity to patent differs across countries, industries and companies
- Differences in patent regulations make it difficult to compare patent counts across countries

- Changes in patent law over the years make it difficult to analyse trends over time

In this study we attributed patents to regions/districts/city agglomerations, which makes it possible to address important policy questions such as:

- The comparative technological performance and profile of regions/city agglomerations
- The importance of geographical proximity for innovation (Jaffe et al., 1993; Audretsch and Feldman, 1996)
- The spatial distribution (or concentration) of innovative activity across regions (e.g. Paci and Usai, 2000)
- Interaction and technological co-operation within and across regions (e.g. Breschi and Lissoni, 2001).

If patents are considered as a main indicator of innovative output in industry, publications are also a good indicator of the innovative effectiveness of the higher education system (Patel and Pavitt, 1995).

PATSTAT contains the bibliographical and legal status of patent data from leading industrialized and developing countries. To retrieve the necessary information from the PATSTAT raw data we used the 14.24 PATSTAT Biblio (raw data) (Edition 2016 - Autumn) version which contains inventor information with country and city names and applicant information. These two datasets were joined. Based on this we sorted data by country and took into consideration Austria and Germany, where we retrieve only inventors from Berlin and Vienna. Belgian data was collected and managed in the following way. We downloaded all data with inventors from Belgium, then sorted this data according to Brussels addresses with different variations of city names. We also considered all possible municipalities in the Brussels region, as this is the case in the address line of PATSTAT database. We joined data with inventors from Brussels with applicant data, where the person code is BE (Belgium only). In the next step we corrected and identified cities. All cities were assigned to one of the regions, city agglomerations and districts. To assign cities to regions/city agglomerations/districts we made a list of cities belonging to every country considered (Brussels, Berlin and Vienna). It should be mentioned that patent data for Brussels, Berlin and Vienna come from the European and US patent offices from 1993-1994 to 2013, which explains why address data is only available for a limited number of patent offices. Specifically, for inventors, as opposed to applicants, they sometimes ask NOT to have their name and address published on the patent document in which case it will not be available in the databases either. However, coverage is reasonably high for EP and US applications (consultation from Geert Boedt, PATSTAT support, Business Use of Patent Information, EPO Vienna).

*Limitations:*

The PATSTAT raw data has some problems in terms of spelling mistakes in the city names which makes the search process more complicated and requires more time to clean and harmonize data.

The main issue we faced was identifying regions/city agglomerations/districts from names of smaller cities, this information requiring much manual search.

The PATSTAT data for Brussels was cleaned according to the city and country's names, with few unrecognizable observations appearing in the sample. Almost all cities were recognized and cleaned. The PATSTAT data for Vienna required some attention due to spelling problems and written mistakes in the country names. The PATSTAT data for Berlin required the same attention as the Austrian data.

### 2.5.3 Number of patent applications with at least one inventor located in Brussels

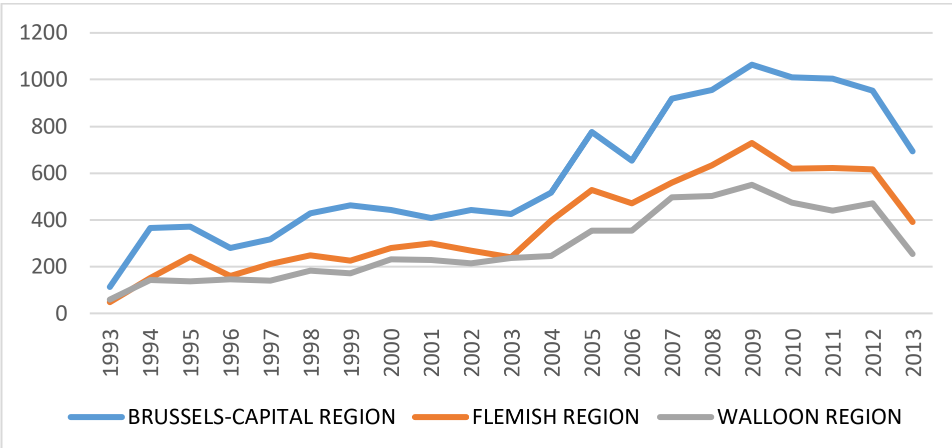
Patent counts provide a measure of invention and innovation output, but patents as indicators of innovative activity are subject to certain drawbacks. However, patent-based indicators should not be discarded as a technological indicator just because of these limitations (van Pottelsberghe et al., 2001). The most commonly used patent-based indicator is the count of patents applied by an organisation (an individual inventor, a private company, a public research organisation, etc.). These counts can be aggregated at a certain spatial level of city, region, country, etc. Patent-counting can also be confined to specific fields of technology.

As a starting point, we illustrate the evolution of the number of patent applications over the period 1993-2013 at the regional level with at least one inventor from the Brussels-Capital Region. We compare this evolution with the other two Belgian regions. To investigate the impact of the economic crisis of 2008 on patenting activity, the period from 1993 to 2013 is split into two sub periods: a pre-crisis sub-period (2000-2008) and a post-crisis one (2009-2013). This indicator is based on the count of patent applications from the databases of EPO and USPTO patent offices. The Brussels-Capital Region for the period 1993-2013 shows a higher patenting activity than the Flemish and Walloon regions. The Flemish Region`s performance over the same period is higher than that of the Walloon Region. These results are not surprising since the analysis is based on patents with inventors located in Brussels. In 2009 all three regions show a peak in the number of patents. After this year we witness a decline in the number of patents per year, which can be explained by the economic crisis (see Figure II-7). A similar situation can be observed in terms of R&D activities in the post-crisis period (2008-2013), where R&D expenditure in the Brussels-Capital Region for most sectors is lower than in the pre-crisis period (2000-2008) (see Section 2 A. Spithoven[11]). From 2012 all regions show a decrease in the number of patent applications. Overall, growth in the pre-crisis period is higher than the situation in the post-crisis period. This might be the consequence of the stimulation of patent activities notably through the launch in 2007 of a new public support scheme granting a tax deduction on licensing income arising from patents

[11] A. Spithoven, 2016 "Regional R&D growth: positioning the Brussels-Capital Region", joint work carried out within the Innoviris and BRUSTI project.

held by Belgian companies (or subsidiaries of foreign multinationals) or on income related to the self-production of goods and services based on this type of patent[12].

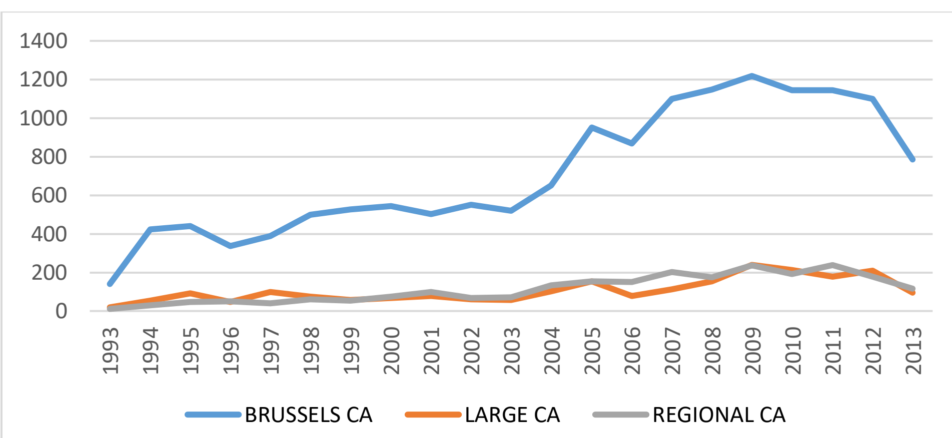
**Figure II-7. Number of patent applications with at least one inventor from Brussels: Evolution over the period 1993-2013 – Brussels-Capital Region compared to the other two Belgian regions**




Source: Own calculations, PATSTAT database
Note: The last two years of data are incomplete, as patent application filing dates are different from publication dates

For further insights, the analysis is also performed at the level of the Brussels city agglomeration (CA) in comparison with the other Large and Regional city agglomerations in Belgium (see Section 3). The analysis is based on the count of patent applications. The Brussels CA indicates the highest patenting activity. We observe a decline in the number of patents after 2009 (see Figure II-8). This negative trend is more severe in Brussels CA than in the other Belgian CAs. The number of patent applications in Large and Regional CAs shows a similar distribution over the period considered.

**Figure II-8. Number of patent applications with at least one inventor from Brussels: Evolution over the period 1993-2013 - Brussels city agglomeration (CA), 4 large city agglomerations (Antwerp, Liege, Gent and Charleroi), and 13 regional city agglomerations**

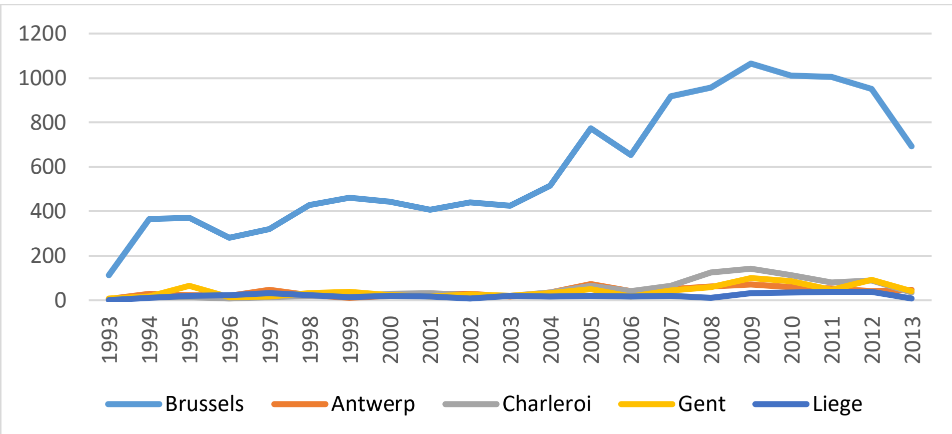



[12] Special Finance Act (Programme Act) of 27 April 2007, 8 May 2007.

Source: Own calculations, PATSTAT database
Note:The last two years of data are incomplete, as patent application filing dates are different from publication dates

A more detailed comparison of the 4 large city agglomerations with Brussels CA is presented in Figure II-9. The methodology used is the same as for previous indicators. According to the number of patent applications, Charleroi and Gent indicate higher figures than Antwerp and Liege. Antwerp presents slightly different results from Gent. All cities show significant growth in patent applications in 2009 and a drop in 2011. In terms of the amount of patent applications, Liege reveals the lowest performance.

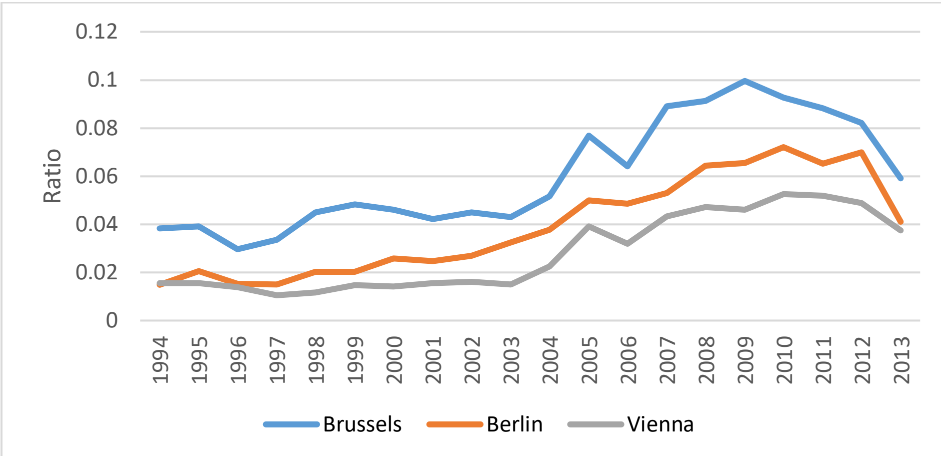
**Figure II-9. Number of patent applications with at least one inventor from the Brussels region: Evolution over the period 1993-2013 of Brussels CA and 4 large city agglomerations (Antwerp, Liege, Gent and Charleroi)**




Source: Own calculations, PATSTAT database
Note: The last two years of data are incomplete, as patent application filing dates are different from publication dates

Next, we compare the ratio of patent applications (Number of patent counts/population) with at least one inventor from Brussels, Berlin or Vienna per 10,000 inhabitants. This benchmark exercise initially developed to compare firm performance, has been progressively transferred and applied to the territorial context, first to national governments, then to European Union policies and to regions (Koellreuter, 2002).

**Figure II-10. Patent applications with at least one inventor per 10,000 inhabitants from Brussels, Berlin and Vienna: Comparison of Brussels with Berlin and Vienna**




Source: Own calculations, PATSTAT database
Note: The last two years of data are incomplete, as patent application filing dates are different from publication dates

For this indicator we also use a patent count methodology for each capital city region. We calculate the indicator in relative terms where we use the population of the capital city regions (Brussels, Berlin and Vienna are considered as mainly relevant at the spatial level of NUTS 2) for the period 1994-2013. The number of patents is divided by the population of Brussels-Capital, Berlin and Vienna regions per 10,000 inhabitants to get a ratio and to be able to make comparative evaluations between the capital city regions. The results in Figure II-10 reveal that the Brussels-Capital Region has a higher performance than Berlin and Vienna regions. The highest performance of the Brussels-Capital Region is found in 2009, and for the Berlin and Vienna regions in 2010. The post–crisis period is characterised by a decline in patent activity with only the Berlin region showing growth in 2011-2012. Referring to Chapter 2.2 A. Spithoven[13], the Berlin region shows a negative advantage in 2000-2013, but a positive effect is observed in the post-crisis period. This fact can potentially explain the growth ratio in 2011-2012 and decline in the economic crisis period. Looking at the Vienna region, the results show a negative regional advantage in all periods as well as the ratio declining in the post-crisis period. The Brussels-Capital Region contributes positively to the general result of the full period in terms of regional advantage.

## 2.5.4 Share of patent applications by organisation (company, government non-profit organisation, individual, university)

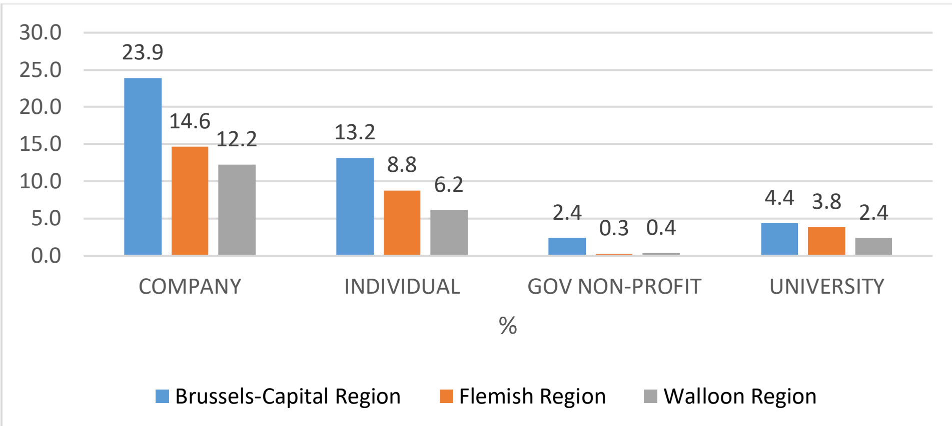
In the context of policy implications, this indicator is useful in identifying trends in patent application distribution according to the type of organisation[14]. In order to produce this indicator,

[13] A. Spithoven, 2016 “Regional R&D growth: positioning the Brussels-Capital Region”, joint work carried out within the Innoviris and BRUSTI project.

[14] Applicants may have been assigned to one or more sectors, such as company, government or non-profit organisation, university or hospital. If the applicant’s sector cannot be determined, then the sector is UNKNOWN. If a person (e.g. a person who is only an inventor, but not an applicant) is not assigned a sector, then this field is empty.
So this column may contain zeroes, one or more of these keywords: INDIVIDUAL, COMPANY, UNKNOWN, GOV
NON-PROFIT, UNIVERSITY, HOSPITAL (PATSTAT, data Catalog)

the number of patent applications for each sector and region was divided by the total number of patent applications with at least one inventor from Brussels for the period 1993-2013, with the results expressed as a percentage.

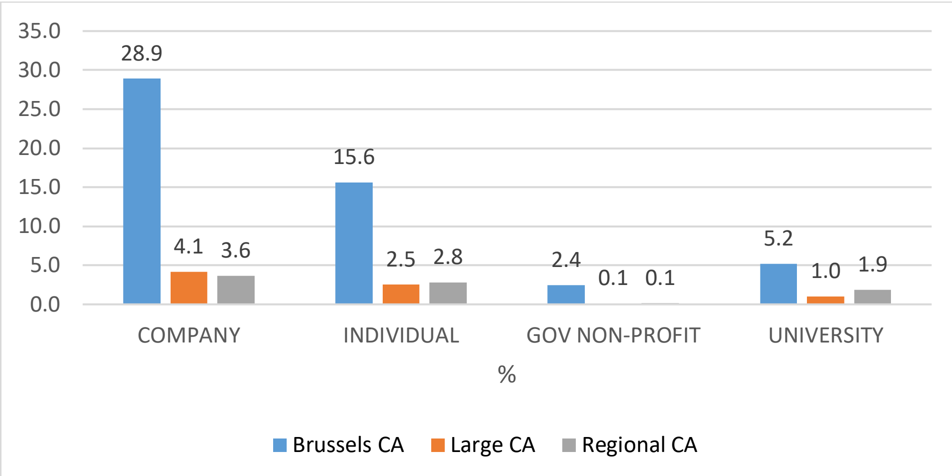
**Figure II-11. Share in % of patent applications by organisation (Company, Government non-profit organisation, Individual, University) with at least one inventor from Brussels (1993-2013) – Brussels-Capital Region compared to the other two Belgian regions**




Source: Own calculations, PATSTAT database.
Note: Unknown observations are not mentioned in the Table (nearly 5%)

At the regional level the highest share of patent applications is in the “Company” and “Individual” sectors. “University” and “Government non-profit” organisations have fewer patent applications. The Brussels-Capital Region shows the highest share of patent applications in the “Company” and “Individual” sectors, while the “University” and “Government non-profit” sectors have the lowest number of applications. Patent distribution in the Flemish region by type of organisation shows that the highest number of patent applications is “Company” and then “Individual”. “University” and “Government non-profit” organisations make significantly less patent applications than the other types of organisations. The Walloon region shows identical trends in the distribution of patent applications to the Brussels-Capital and Flemish regions. The Brussels-Capital region has a higher share of patents from “University” than the Flemish Region, with the Walloon region having only half as many patent applications in this institutional sector. In general, the Walloon Region has the lowest share of patent applications in all types of organisations, almost half the other two regions. The results reveal that universities and government non-profit organisations are less likely to patent than companies and individuals at the regional level, which can be explained by the particularly expensive and difficult process of patent application. According to our calculations, for the period of 1990-2015 around 51% of all patent applications with at least one inventor from Brussels come from companies and 27% from individual inventors. Only 13% come from academic institutions, RTOs, and government agencies.

**Figure II-12. Share in % of patent applications by organisation (Company, Government non-profit organisation, Individual, University) with at least one inventor from Brussels (1993-2013) - Brussels city agglomeration (CA), 4 large city agglomerations (Antwerp, Liege, Gent and Charleroi), and 13 regional city agglomerations**

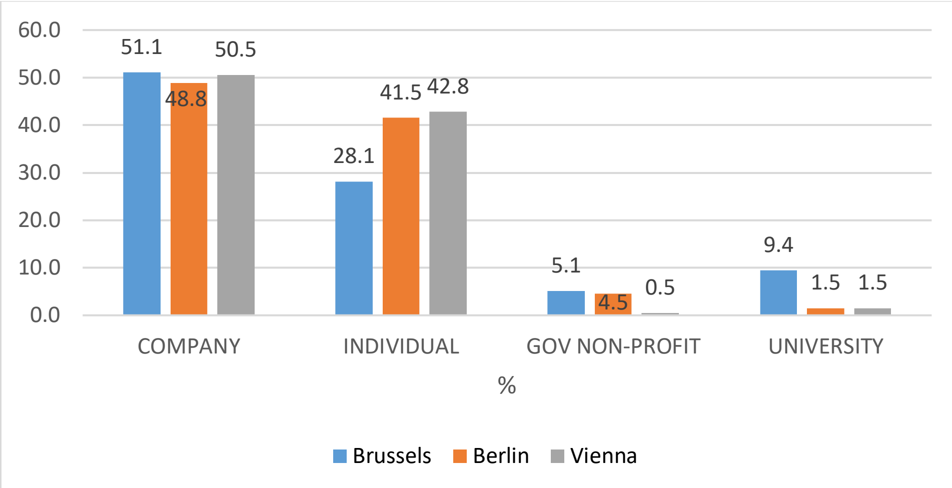



Source: Own calculations, PATSTAT database

Comparing city agglomeration levels (CA), it is observed that the highest share of patent applications among CAs belongs to the “Company “and “Individual” sectors. Since the analysis is based on patents with inventors located in Brussels, Brussels CA is more represented than the other CAs in all types of organisations. Large and Regional CAs reveal a similar distribution of patent applications among different sectors. Hence, in the “Individual” type of organisation, large CAs have the smallest share of patent applications, in comparison with Regional CAs. The lowest performance in terms of patent applications in the “University” sector is in large CAs.

To extend the analysis, we also compared the shares of patent applications by organisation with at least one inventor from Brussels, Berlin and Vienna respectively.

**Figure II-13. Share in % of patent applications by organisation (Company, Government non-profit organisation, Individual, University) with at least one inventor from Brussels, Berlin and Vienna (1993-2013): Comparison of Brussels with Berlin and Vienna**




Source: Own calculations, PATSTAT database
Note: Total share by the capital city region is not equal to 100%, as share of other regions is not included. Unknown observations as % are not mentioned in the Figure, nor is the share of not identified observations

Figure II-13 reveals a similar distribution of patent applications among sectors as in previous indicators, the highest distribution of patent applications being in the “Company” and “Individual” sectors. The Brussels region reveals the highest performance in “Company”, “Government non-profit” and “University” sectors. The “Company” sector shows that the difference between metropolitan regions is rather small in comparison with the “University” sector, where Berlin and Vienna have a much smaller distribution than the Brussels region. The most active region in the “Individual” sector is Vienna, with Berlin showing a slightly lower distribution. Vienna has the lowest share in the “Government non-profit” sector, with Brussels and Berlin regions having similar shares.

In Section 2.5.4 we observed a clear tendency of how regions, city agglomerations and capital city regions distribute their patents in the four sectors. Whichever spatial level we test, the “Company” and “Individual” sectors hold the highest number of patents among regions/city agglomeration/capital city regions. However, “University” and “Government non-profit” organisations tend to patent less. The conclusion is twofold: over time companies are more able and willing to produce patents than universities or government non-profit organisations, due to the costly, drawn-out process of patenting. And secondly, this also depends on the level of R&D activities, as if firms spend more on R&D than universities (which is the case), they will also file more patents, which explains the propensity to patent.

### 2.5.5 Relative share of top IPC classes

Relative share of top IPC classes[15] as an indicator requires additional attention. In order to produce this indicator, we manipulated the data and their interpretation to some extent. The two-digit International Patent Classification (118 classes) allows identification of the technological fields of patent applications. To facilitate interpretation, the 118 IPC classes were grouped into 50 broad classes (Cincera, 1998). According to the smart specialisation approach, we constructed three other IPC classes (Health, ICT and Environment). It should be mentioned that these IPC classes are strategic action domains incorporated in the Regional Innovation Plan 2016-2020. The aggregation was made using the following IPC codes:

- ICT: A63, B81, B82, G01, G02, G11, H01, H02, H03, H04, H05
- Environment: B03, B07, B08, B09, C01, C02, C03, C04, C25, E03, E04, E05, E06, E21, F15, F17, H01, H02, H03
- Health: A61, B02, B03, B04, C23, D03, D04, D06, G01, G02

To produce the "relative share of top IPC classes" indicator, the number of patent applications by IPC class is multiplied by 100 (weighted share) and divided by the total sum of patent counts for all IPC classes.

**Table II-2. Relative share of top IPC classes (1993-2013) – Brussels-Capital Region compared to other Belgian regions**

| IPC classes | Brussels-Capital region | Flemish region | Walloon region |
|---|---|---|---|
| MEDICAL AND VETERINARY SCIENCE; LIFE-SAVING | 10.82 | 5.51 | 5.29 |
| FERTILISERS; ORGANIC CHEMISTRY | 4.08 | 2.58 | 2.12 |
| ORGANIC MACROMOLECULAR COMPOUNDS | 3.50 | 1.77 | 2.45 |
| COMPUTING; CALCULATING | 3.18 | 1.82 | 0.40 |
| PHYSICAL AND CHEMICAL PROCESSES AND APPARATUS | 2.64 | 1.62 | 2.19 |
| ELECTRIC COMMUNICATION TECHNIQUE | 1.80 | 1.41 | 0.16 |
| WORKING OF PLASTICS | 1.57 | 0.99 | 0.99 |
| BASIC ELECTRIC ELEMENTS | 1.51 | 1.89 | 0.49 |
| MEASURING; TESTING | 1.43 | 0.92 | 0.53 |
| ANIMAL AND VEGETABLE OILS | 1.34 | 1.30 | 0.31 |
| HEALTH | 11.17 | 5.73 | 5.66 |
| ICT | 5.76 | 5.28 | 1.56 |
| ENVIRONMENT | 2.51 | 1.27 | 1.44 |

Source: Own calculations, PATSTAT database

[15]IPC CLASS SYMBOL - Classification symbol according to the International Patent Classification, eighth edition (coming into force on January 1, 2006), provides for a hierarchical system of language independent symbols for the classification of patents and utility models according to the different areas of technology to which they pertain.

According to the regional comparison with at least one inventor from Brussels, “medical and veterinary science; life-saving” class has the highest share of IPC class. The Brussels-Capital Region presents a higher share than the other two regions. The “Basic electric elements” class has the highest value in the Flemish Region. In most cases, the Flemish Region performs better than the Walloon Region, with only “organic macromolecular compounds” and “working of plastics” having higher or similar values. Moreover, the “Health” IPC class shows better performance than the “ICT” and the “Environment” classes in the Brussels-Capital Region. However, the “ICT” class is slightly different between the Flemish and Brussels-Capital Regions.

Our results show that “medical and veterinary science; life-saving” and “health” technological fields are the predominant areas at the spatial levels considered. This can be explained by the Western model, which is the characteristic pattern of developed Western countries with clinical medicine and biomedical research as the dominant fields (Glänzel, 2000).

**Table II-3. Relative share of top IPC classes (1993-2013) - Brussels city agglomeration (CA), 4 large city agglomerations (Antwerp, Liege, Gent and Charleroi), and 13 regional city agglomerations**

| IPC classes | Brussels CA | Large CA | Regional CA |
|---|---|---|---|
| MEDICAL AND VETERNIANRY SCIENCE; LIFE-SAVING | 13.20 | 1.69 | 1.60 |
| FERTILISERS; ORGANIC CHEMISTRY | 4.88 | 0.84 | 0.63 |
| ORGANIC MACROMOLECULAR COMPOUNDS | 4.40 | 0.37 | 0.62 |
| COMPUTING; CALCULATING | 3.47 | 0.43 | 0.69 |
| PHYSICAL AND CHEMICAL PROCESSES AND APPARATUS | 3.32 | 0.37 | 0.57 |
| WORKING OF PLASTICS | 2.08 | 0.26 | 0.12 |
| ELECTRIC COMMUNICATION TECHNIQUE | 1.87 | 0.44 | 0.31 |
| ANIMAL AND VEGETABLE OILS | 1.74 | 0.16 | 0.19 |
| BASIC ELECTRIC ELEMENTS | 1.64 | 0.20 | 1.24 |
| MEASURING; TESTING | 1.56 | 0.21 | 0.46 |
| HEALTH | 13.51 | 1.80 | 1.66 |
| ICT | 6.17 | 1.10 | 2.35 |
| ENVIRONMENT | 3.09 | 0.60 | 0.33 |

Source: Own calculations, PATSTAT database

In this sub-section we further refined our research and made a comparison at the city agglomeration level. The top IPC class is “medical and veterinary science; life-saving” and the leading position belongs to Brussels CA. Large and Regional CA shares in “medical and veterinary science; life-saving “class are slightly different. Regional CA shows a higher value than Large CA in the “basic electric elements” class. In addition, “Health” IPC class has a higher performance than “ICT” and

"Environment" IPC classes. "Environment" IPC class presents the lowest performance (see Table II-3).

**Table II-4. Relative share of top IPC classes (1993-2013): Comparison of Brussels with Berlin and Vienna**

| IPC classes | Brussels | Berlin | Vienna |
|---|---|---|---|
| MEDICAL AND VETERNIANRY SCIENCE; LIFE-SAVING | 10.82 | 16.78 | 2.14 |
| FERTILISERS; ORGANIC CHEMISTRY | 4.08 | 0.27 | 1.99 |
| ORGANIC MACROMOLECULAR COMPOUNDS | 3.50 | 2.81 | 0.30 |
| COMPUTING; CALCULATING | 3.18 | 4.28 | 0.59 |
| PHYSICAL AND CHEMICAL PROCESSES AND APPARATUS | 2.64 | 1.46 | 0.46 |
| ELECTRIC COMMUNICATION TECHNIQUE | 1.80 | 3.36 | 0.28 |
| WORKING OF PLASTICS | 1.57 | 0.21 | 0.73 |
| BASIC ELECTRIC ELEMENTS | 1.51 | 5.01 | 0.59 |
| MEASURING; TESTING | 1.43 | 3.53 | 0.93 |
| ANIMAL AND VEGETABLE OILS | 1.34 | 0.05 | 0.21 |
| Health | 11.17 | 17.72 | 23.83 |
| ICT | 5.76 | 14.80 | 10.77 |
| Environment | 2.51 | 1.39 | 0.73 |

Source: Own calculations, PATSTAT database

The comparison between capital city regions is presented in Table II-4. This shows that "medical and veterinary science; life-saving" IPC class has the highest performance in Berlin, with Vienna having the lowest value. In other IPC classes such as "computing; calculating", "electric communication technique", "basic electric elements" and "measuring; testing" Berlin performed better then Brussels and Vienna. All shares of IPC classes are lower in Vienna than in Brussels and Berlin. However, we can see that Vienna reveals the highest performance in the Health IPC class. Berlin performs better in the ICT class than Brussels and Vienna. In the Environment IPC class, Brussels has the highest indicator.

## 2.5.6 Technological proximities within and across industries

Technological proximities between districts give a picture of how patents by IPC field are distributed and concentrated (Herfindahl index[16]) across geographic areas as well as industry sectors (Cincera and Capron, 2003). Locating firms into the technological space allows assessment of the importance of technological spillovers as well. Indeed, this way of formalising spillovers is closely related to the notion of technological proximity: the closer two firms are in the

[16] The Herfindahl-Hirschman index (HHI) is a commonly accepted measure of market concentration. It is calculated by squaring the market share of each firm competing in a market, and then summing the resulting numbers, and can range from close to zero to 10,000.

technological space, the more the research activity of one firm is supposed to be affected by the technological spillovers generated by the research activities of the other. Hence, it is assumed that each firm faces a potential ‘stock’ of spillovers, which is a weighted sum of the technological activities undertaken by all other firms. To measure the technological closeness between firm i and j, Jaffe (Jaffe, A.B., 1986) used the ‘angular separation’ between them, i.e. he computed the uncentered correlation between their respective vectors of technological position:

$$\mathbf{T}_j = (\mathbf{t}_{j1}, \ldots, \mathbf{t}_{jK})$$

$$P_{ij} = \frac{\sum_{k=1}^{K} T_{ik} T_{jk}}{\sqrt{\sum_{k=1}^{K} T_{ik}^2 \sum_{k=1}^{K} T_{jk}^2}}$$

This measure of closeness takes values between one and zero according to the common degree of research interest of both firms (Cincera, 2005). Thanks to the classification of patent data by patent fields or technological classes, it is possible to measure the technological proximity between firms by characterizing their positions in the technological space.

**Table II-5. Technological proximities within and across industries (1993-2013): comparison of Brussels with metropolitan regions of Belgium (case of 4 districts (Antwerp, Liege, Gent and Charleroi)**

| | Antwerp | Brussels | Gent | Charleroi | Liege | HHI |
|---|---|---|---|---|---|---|
| Antwerp | 1 | | | | | 0.08 |
| Brussels | 0.84 | 1 | | | | 0.08 |
| Gent | 0.57 | 0.86 | 1 | | | 0.12 |
| Charleroi | 0.56 | 0.71 | 0.56 | 1 | | 0.09 |
| Liege | 0.64 | 0.93 | 0.80 | 0.67 | 1 | 0.11 |

Source: own calculations, PATSTAT database, OECD, Eurostat

| | Antwerp | Mechelen | Turnhout | Brussels | Leuven | Brugge | Kortrijk | Oostende | Gent | Sint-Niklaas | Charleroi | Mons | Doornik | Liege | Verviers | Namur | HHI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Antwerp | 1 | | | | | | | | | | | | | | | | 0.08 |
| Mechelen | 0.97 | 1 | | | | | | | | | | | | | | | 0.07 |
| Turnhout | 0.52 | 0.69 | 1 | | | | | | | | | | | | | | 0.16 |
| Brussels | 0.84 | 0.85 | 0.88 | 1 | | | | | | | | | | | | | 0.08 |
| Leuven | 0.69 | 0.73 | 0.64 | 0.79 | 1 | | | | | | | | | | | | 0.09 |
| Brugge | 0.45 | 0.58 | 0.40 | 0.55 | 0.59 | 1 | | | | | | | | | | | 0.09 |
| Kortrijk | 0.74 | 0.60 | 0.46 | 0.58 | 0.55 | 0.51 | 1 | | | | | | | | | | 0.05 |
| Oostende | 0.50 | 0.76 | 0.86 | 0.85 | 0.67 | 0.32 | 0.42 | 1 | | | | | | | | | 0.18 |
| Gent | 0.57 | 0.69 | 0.85 | 0.86 | 0.61 | 0.63 | 0.63 | 0.69 | 1 | | | | | | | | 0.12 |
| Sint-Niklaas | 0.96 | 0.84 | 0.56 | 0.74 | 0.56 | 0.41 | 0.49 | 0.66 | 0.57 | 1 | | | | | | | 0.06 |
| Charleroi | 0.56 | 0.54 | 0.54 | 0.71 | 0.54 | 0.52 | 0.46 | 0.42 | 0.56 | 0.52 | 1 | | | | | | 0.09 |
| Mons | 0.57 | 0.71 | 0.82 | 0.90 | 0.65 | 0.39 | 0.36 | 0.73 | 0.71 | 0.64 | 0.77 | 1 | | | | | 0.13 |
| Doornik | 0.40 | 0.56 | 0.60 | 0.76 | 0.58 | 0.36 | 0.36 | 0.48 | 0.60 | 0.50 | 0.74 | 0.87 | 1 | | | | 0.20 |
| Liege | 0.64 | 0.71 | 0.93 | 0.93 | 0.74 | 0.44 | 0.46 | 0.81 | 0.80 | 0.60 | 0.67 | 0.89 | 0.73 | 1 | | | 0.11 |
| Verviers | 0.54 | 0.59 | 0.77 | 0.75 | 0.56 | 0.32 | 0.43 | 0.66 | 0.65 | 0.56 | 0.56 | 0.67 | 0.57 | 0.79 | 1 | | 0.10 |
| Namur | 0.60 | 0.76 | 0.91 | 0.94 | 0.70 | 0.44 | 0.39 | 0.84 | 0.77 | 0.66 | 0.72 | 0.94 | 0.76 | 0.95 | 0.75 | 1 | 0.13 |

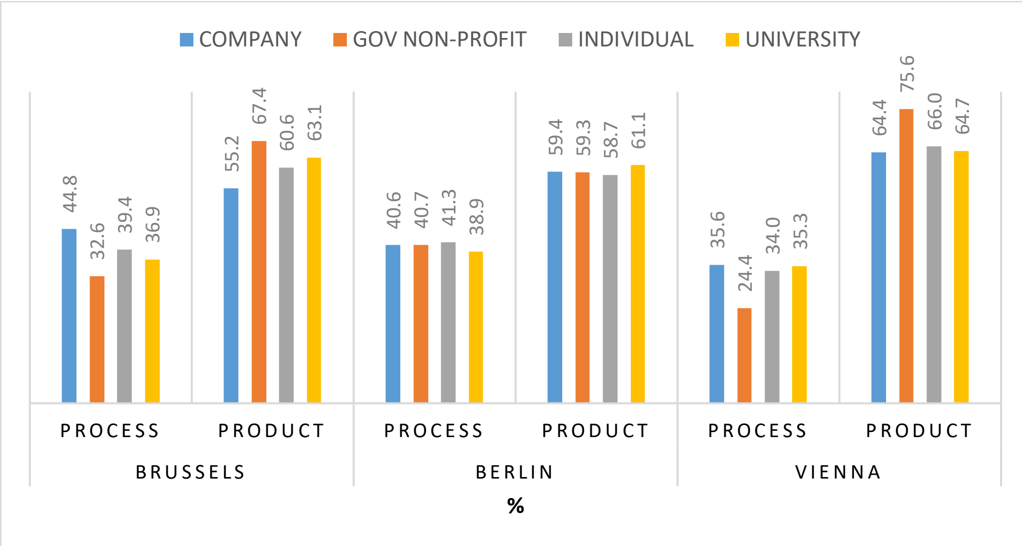
Source: own calculations, PATSTAT database, OECD, Eurostat

According to Table II-5, Brussels reveals the highest technological proximities with Namur, Liege, Mons, Gent, Oostende and Antwerp. It has the lowest technological proximities with Leuven, Brugge, Kortrijk, Sin-Niklaas, Verviers, Charleroi and Hasselt. Antwerp in general has weak technological proximities with most of the districts, but the strongest technological proximities are with Mechelen, Brussels and Sint-Niklaas districts. Gent district has the strongest technological proximities with Turnhout, Brussels and Liege, the other districts revealing weaker technological proximities. For example, Charleroi shows weak technological proximities with most districts. The highest HHI indices are achieved is by Oostende, Gent, Mons, Namur and Doornik. The higher the Herfindhal index in a district, the lower its level of technological diversification. Looking at the off-diagonal cells, Table II-5 gives an idea of how technologically distant the districts are. Moreover, the technological distances reported in Table II-5 seem to be consistent with reality.

### 2.5.7 Patent distribution by the type of innovation

Technological change can be defined in several ways. It is very common to distinguish process innovation from product innovation.  In the work of Cincera and Capron (2003) the private rates of return are higher for processes than for products, although product innovations are more favourable to job creation than process innovations, which mainly improve productivity. Furthermore, a considerable part of R&D expenditure goes to product innovation. A logometric analysis of the summary of each patent applied from the PATSTAT database is made. Each time the word “process” and/or “method” are found, the patent application is assigned to a process invention. Then we calculate the shares of the type of innovation for each capital city region.

**Figure II-14. Patent distribution by the type of innovation in % (1993-2013) (product and process): Comparison of Brussels with Berlin and Vienna**




Source: Own calculations, PATSTAT database

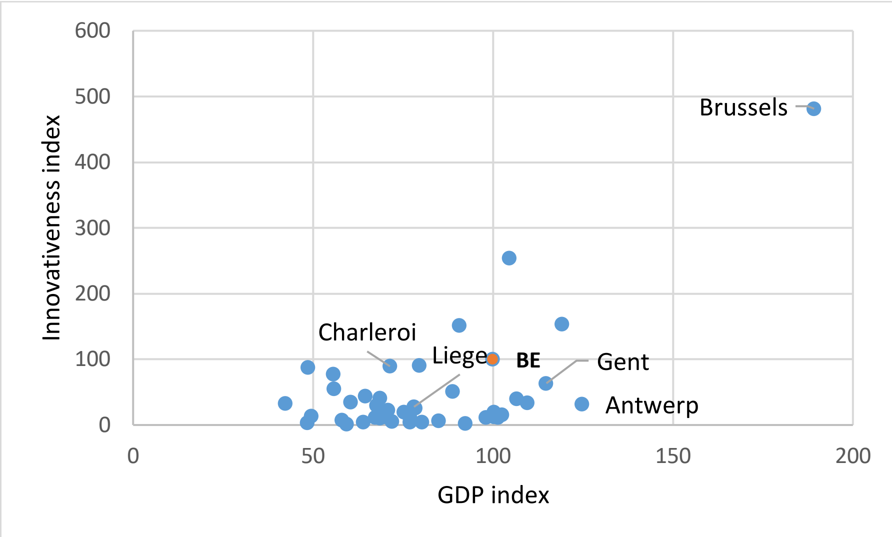
Figure II-14 suggests that the prevailing patent applications over the period are product patents in all the cities considered. Additionally, we can see the distribution of product/process patent applications among different types of organisations. Vienna presents the highest share of product-oriented patent applications in all types of organisations. We can also see that the share of product-oriented innovations is significantly higher than process-oriented innovations. In Berlin capital city region, the distribution of shares among process and product innovations is less distinct, although product innovations have a bigger share. Brussels reveals a similar distribution in the type of innovation to Vienna. The distribution of patents between these two categories does not seem to have changed drastically over time.

The next indicator presented shows the levels of concentration of innovativeness regarding patents in Belgian districts.

## 2.5.8 Concentration of innovativeness and wealth at the district level

The methodology used to construct the indicator of Concentration of innovativeness and wealth at the district level has a different approach in terms of spatial aggregation. All districts were organised at the NUTS 3 level by EUROSTAT aggregation as GDP is only available for this agglomeration (EUROSTAT, NUTS3). To build this indicator we construct two different variables. The first variable is the Innovativeness index which is calculated as R&D intensity by district multiplied by 100 and divided by the R&D intensity of Belgium. The second variable is the GDP index which is calculated as GDP per capita by district multiplied by 100 and divided by the GDP per capita of Belgium.

**Figure II-15. Concentration of innovativeness and wealth at the district level (Brussels and metropolitan regions of Belgium) (Belgium = 100, average 1993-2013)**




Source: own calculations, PATSTAT database, OECD, Eurostat

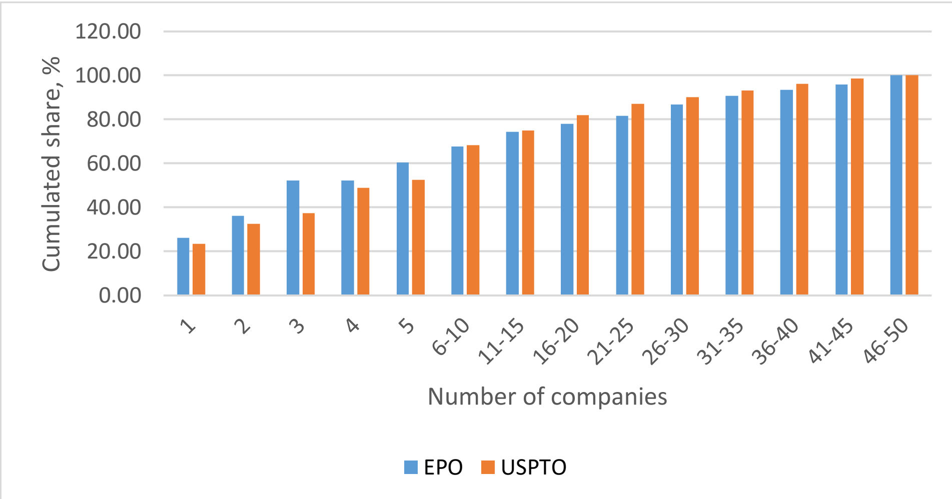
As seen from these figures, Nivelles, Hal-Vilvoorde and Brussels are the three main patenting districts in Belgium. The Innovativeness index[17]of Liege is slightly above the Belgian average, while Charleroi, Waremme and Namur are slightly below that average. Charleroi, Namur and Liege have a higher innovativeness index than Gent and Antwerp but a lower GDP index[18]. Turnhout and Antwerp have the same level of innovativeness index, but the GDP index is higher in Antwerp. Overall, all the other districts have a share under 5%.

[17]Innovativeness index = R&D intensity by district I *100/(number of patents for BE/average population of BE), where R&D intensity by district = number of patents by district/average population by district

[18]GDP index = GDP per capita by district i *100/(GDP average of BE/average population of BE), where GDP per capita=GDP average by district/average population by district.

### 2.5.9 Cumulated distribution of the number of patent applications of the top 50 Belgian firms

**Figure II-16. Cumulated distribution of the number of patent applications of the top 50 Belgian firms (EPO and USPTO, 1993- 2014)**




Source: Own calculations, PATSTAT database

Figure II-16 sheds some light on the patenting activities of the top 50 Belgian firms. As observed, this activity is quite concentrated. The cumulated share of US patents of the top 50 Belgian firms is slightly higher than European patents. This reveals that the largest firms patent mainly outside the European market. As mentioned in the work of Cincera and Capron (2003) Belgian patent activity is highly dependent on a few companies, most of which are subsidiaries of foreign multinationals. The lower tendency to patent can be explained by the greater dependency of the Belgian innovation system on foreign multinationals. Thus, Belgian subsidiaries are specialised in the adaptation to the European market of products and processes developed in foreign headquarters of multinationals. Head offices could also be hoarding a significant part of their R&D output, with foreign firms taking advantage of the local availability of a highly qualified workforce and knowledge base (Cincera and Capron, 2003).

### 2.5.10 Revealed Technology Advantage (RTA)

Patents are used to monitor the technological performance of countries, regions or organisations. Patents are a more appropriate indicator to assess activities closer to technology development compared to publication indicators. Patents, as indicators of technological performance, help researchers and policy makers to identify weak and strong areas in national or regional innovation systems (Manual, O.P.S., 2009). The identification of technology domains and industries in patent data makes it possible to analyse the technological position of a country/region/district relative to others or to the world average.

According to the OECD Patent Statistics Manual, 2009 the “Revealed technological advantage” (RTA) index is defined as the share of a country **i** in patents **P** in a field of technology **d** divided by the country’s share in all patents:

$$\mathrm{RTA} = \frac{\left(P_{d,i} / \sum_{d} P_{d,i}\right)}{\left(\sum_{di} P_{d,i} / \sum_{d,i} P_{d,i}\right)}$$

The index is equal to zero when the country holds no patents in a given sector, and equal to 1 when the country’s share in the sector is equal to its share in all fields (no specialisation) and grows rapidly (the upper limit will depend on the world distribution used) when a positive specialisation is found. Figures based on RTA indicators must be interpreted with caution, especially for international comparisons. A country with a very large total patent output will tend to have all its RTAs close to 1, whereas a country with a low patent output will have a very high value for the fields in which its output is slightly higher than the average for the country.

A revealed technological advantage (RTA) index, built from the PATSTAT database, provides an indication of a given economy's relative specialisation in various technology domains. According to the results of the RTA index in the top three IPC classes (with the highest share of patent applications), the Brussels-Capital Region has a technological advantage in “Computing; calculating - 1.27” IPC class, while “Medical and veterinary science – 0.97; and “Life-saving - 0.96” do not reveal a technological advantage over the period 1993-2013. The distribution of the RTA indexes among the top 3 IPC classes with the highest share of patent applications in the Flemish Region shows a technological advantage in “Basic electric elements - 1.59”, while “Medical and veterinary science – 0.94”; “Life-saving-0.97” IPC classes do not indicate any revealed advantage. As for the Walloon Region, the RTA index in the top three IPC classes shows a technological advantage in all top three IPC classes: “Medical and veterinary science – 1.14”, “Life-saving - 1.07” and “Organic macromolecular compounds - 1.39”, while the IPC class “Presses; paper; layered products” shows the highest RTA index of other IPC classes. In conclusion, the Brussels-Capital and Walloon regions apply relatively more patents in the field of health, environment, chemistry and pharmaceuticals while the Flemish region seems to be more specialised in the field of instruments and ICT. It should be mentioned that these technological classes are precisely the ones for which patenting is the most effective.

**Table II-6. Revealed technology advantage (RTA) in selected fields with at least one inventor from Brussels by Top 10 IPC classes – Brussels-Capital Region compared to the other Belgian regions**

| IPC class | Brussels - Capital region | IPC class | Flemish region | IPC class | Walloon region |
|---|---|---|---|---|---|
| MEDICAL AND VETERNIANRY SCIENCE; LIFE-SAVING | 0.97 | MEDICAL AND VETERNIANRY SCIENCE; LIFE-SAVING | 0.94 | MEDICAL AND VETERNIANRY SCIENCE; LIFE-SAVING | 1.14 |
| FERTILISERS; ORGANIC CHEMISTRY | 0.96 | FERTILISERS; ORGANIC CHEMISTRY | 0.97 | FERTILISERS; ORGANIC CHEMISTRY | 1.07 |
| COMPUTING; CALCULATING | 1.27 | BASIC ELECTRIC ELEMENTS | 1.59 | ORGANIC MACROMOLECULAR COMPOUNDS | 1.39 |
| ORGANIC MACROMOLECULAR COMPOUNDS | 0.97 | COMPUTING; CALCULATING | 1.08 | PHYSICAL AND CHEMICAL PROCESSES AND APPARATUS | 1.39 |
| PHYSICAL AND CHEMICAL PROCESSES AND APPARATUS | 0.88 | PHYSICAL AND CHEMICAL PROCESSES AND APPARATUS | 0.85 | WORKING OF PLASTICS | 1.34 |
| BASIC ELECTRIC ELEMENTS | 0.86 | ORGANIC MACROMOLECULAR COMPOUNDS | 0.74 | PRESSES; PAPER;LAYERED PRODUCTS | 1.71 |
| MEASURING; TESTING | 1.06 | ELECTRIC COMMUNICATION TECHNIQUE | 1.31 | BIOCHEMISTRY; SUGAR | 1.40 |
| ELECTRIC COMMUNICATION TECHNIQUE | 1.17 | ANIMAL AND VEGETABLE OILS | 1.50 | AGRICULTURE | 1.50 |
| WORKING OF PLASTICS | 0.95 | MEASURING; TESTING | 1.09 | MILLING; CLEANING; DISPOSAL OF SOLID WASTE | 1.02 |
| MILLING; CLEANING; DISPOSAL OF SOLID WASTE | 1.00 | MILLING; CLEANING; DISPOSAL OF SOLID WASTE | 1.01 | MEASURING; TESTING | 0.77 |
| ***Health*** | 0.97 | ***Health*** | 0.94 | ***Health*** | 1.13 |
| ***ICT*** | 0.98 | ***ICT*** | 1.39 | ***ICT*** | 0.56 |
| ***Environment*** | 1.05 | ***Environment*** | 0.85 | ***Environment*** | 1.12 |

Source: Own calculations, PATSTAT database

The next step was to compare city agglomerations (see Table II-7). According to the Top three IPC classes with the highest share of patent applications the Brussels CA indicates a technological advantage only in two IPC classes; "Medical and veterinary science; life-saving – 1.00" and

“Fertilisers; organic chemistry – 1.04”. The results show that the RTA indexes of Large CAs in the three Top IPC classes (presented in descending order with the highest share of patent applications) have a technological advantage only in “Medical and veterinary science; life-saving- 1.00” and “Fertilisers; organic chemistry - 1.04”. The RTA indexes in the Regional CA show a technological advantage in the 3 Top IPC classes only in “Basic electric elements - 3.36” and “Computing; calculating - 1.27”. The Brussels CA and Walloon CA apply relatively more patents in the field of health and environment while the Regional CA seems to be more specialised in the field of ICT.

**Table II-7. Revealed technology advantage in selected fields with at least one inventor from Brussels by Top 10 IPC classes - Brussels city agglomeration (CA), 4 large city agglomerations (Antwerp, Liege, Gent and Charleroi), and 13 regional city agglomerations**

| IPC class | Brussels CA | IPC class | Large CA | IPC class | Regional CA |
|---|---|---|---|---|---|
| MEDICAL AND VETERINARY SCIENCE; LIFE-SAVING | 1.00 | MEDICAL AND VETERINARY SCIENCE; LIFE-SAVING | 1.00 | MEDICAL AND VETERINARY SCIENCE; LIFE-SAVING | 0.94 |
| FERTILISERS; ORGANIC CHEMISTRY | 1.04 | FERTILISERS; ORGANIC CHEMISTRY | 1.04 | BASIC ELECTRIC ELEMENTS | 3.36 |
| COMPUTING; CALCULATING | 0.99 | COMPUTING; CALCULATING | 0.99 | COMPUTING; CALCULATING | 1.27 |
| ORGANIC MACROMOLECULAR COMPOUNDS | 2.32 | PRESSES; PAPER;LAYERED PRODUCTS | 2.32 | FERTILISERS; ORGANIC CHEMISTRY | 0.74 |
| PHYSICAL AND CHEMICAL PROCESSES AND APPARATUS | 1.50 | ELECTRIC COMMUNICATION TECHNIQUE | 1.50 | PHYSICAL AND CHEMICAL PROCESSES AND APPARATUS | 1.04 |
| BASIC ELECTRIC ELEMENTS | 4.33 | GLASS; CEMENTS | 4.33 | ORGANIC MACROMOLECULAR COMPOUNDS | 0.88 |
| MEASURING; TESTING | 0.65 | ORGANIC MACROMOLECULAR COMPOUNDS | 0.65 | MEASURING; TESTING | 1.50 |
| WORKING OF PLASTICS | 0.66 | PHYSICAL AND CHEMICAL PROCESSES AND APPARATUS | 0.66 | BIOCHEMISTRY; SUGAR | 1.31 |
| ELECTRIC COMMUNICATION TECHNIQUE | 1.28 | MILLING; CLEANING; DISPOSAL OF SOLID WASTE | 1.28 | MILLING; CLEANING; DISPOSAL OF SOLID WASTE | 1.05 |
| MILLING; CLEANING; DISPOSAL OF SOLID WASTE | 1.22 | BIOCHEMISTRY; SUGAR | 1.22 | ELECTRIC COMMUNICATION TECHNIQUE | 0.90 |

| IPC class | Brussels CA | IPC class | Large CA | IPC class | Regional CA |
|---|---|---|---|---|---|
| ***Health*** | 1.00 | ***Health*** | 1.01 | ***Health*** | 0.94 |
| ***ICT*** | 0.89 | ***ICT*** | 0.97 | ***ICT*** | 2.03 |
| ***Environment*** | 1.11 | ***Environment*** | 1.33 | ***Environment*** | 0.74 |

Source: Own calculations, PATSTAT database

Table II-8 presents the RTA index of three comparable city regions over pre- (2000-2008) and post-crisis (2009-2013) periods.

**Table II-8. Revealed technology advantage in selected fields with at least one inventor from Brussels by Top 10 IPC classes: Comparison of Brussels with Berlin and Vienna**

| | **Brussels** | | |
|---|---|---|---|
| **RTA index** | **IPC class** | **2000-2008** | **2009-2013** |
| | MEDICAL AND VETERNIANRY SCIENCE; LIFE-SAVING | 0.97 | 0.98 |
| | FERTILISERS; ORGANIC CHEMISTRY | 1.06 | 0.89 |
| | ORGANIC MACROMOLECULAR COMPOUNDS | 0.99 | 0.94 |
| | COMPUTING; CALCULATING | 1.36 | 1.20 |
| | PHYSICAL AND CHEMICAL PROCESSES AND APPARATUS | 0.94 | 0.83 |
| | MEASURING; TESTING | 1.08 | 1.03 |
| | ELECTRIC COMMUNICATION TECHNIQUE | 1.04 | 1.30 |
| | WORKING OF PLASTICS | 0.94 | 0.96 |
| | BASIC ELECTRIC ELEMENTS | 0.80 | 0.89 |
| | AGRICULTURE | 0.84 | 0.62 |
| | **Berlin** | | |
| **RTA index** | **IPC class** | **2000-2008** | **2009-2013** |
| | MEDICAL AND VETERNIANRY SCIENCE; LIFE-SAVING | 0.96 | 0.96 |
| | BASIC ELECTRIC ELEMENTS | 1.17 | 0.98 |
| | COMPUTING; CALCULATING | 0.94 | 1.18 |
| | MEASURING; TESTING | 1.06 | 1.05 |
| | ELECTRIC COMMUNICATION TECHNIQUE | 0.87 | 1.22 |
| | AGRICULTURE | 0.85 | 0.68 |
| | PHYSICAL AND CHEMICAL PROCESSES AND APPARATUS | 0.96 | 0.82 |
| | FERTILISERS; ORGANIC CHEMISTRY | 1.05 | 0.98 |
| | MILLING; CLEANING; DISPOSAL OF SOLID WASTE | 1.14 | 0.97 |
| | BIOCHEMISTRY; SUGAR | 1.12 | 1.13 |
| | **Vienna** | | |
| **RTA index** | **IPC class** | **2000-2008** | **2009-2013** |
| | MEDICAL AND VETERNIANRY SCIENCE; LIFE-SAVING | 1.10 | 1.12 |
| | COMPUTING; CALCULATING | 1.22 | 1.18 |
| | ELECTRIC COMMUNICATION TECHNIQUE | 1.16 | 1.09 |
| | AGRICULTURE | 1.05 | 1.25 |
| | BIOCHEMISTRY; SUGAR | 0.95 | 1.19 |
| | FERTILISERS; ORGANIC CHEMISTRY | 0.96 | 1.05 |
| | MEASURING; TESTING | 0.94 | 1.12 |
| | BASIC ELECTRIC ELEMENTS | 0.95 | 0.79 |
| | GENERATION, CONVERSION | 1.08 | 0.99 |
| | PHYSICAL AND CHEMICAL PROCESSES AND APPARATUS | 0.87 | 1.01 |

Source: own calculations, PATSTAT database

The largest IPC class “Medical and veterinary science; life-saving”, according to specialisation performance, shows that in the Brussels-Capital Region there is a slight change in the RTA index in the post-crisis period compared to the pre-crisis period. The Berlin region indicates no change in specialisation performance over the two periods and the Vienna region presents a slight change in the RTA index in the post–crisis period.

With regard to the top 10 IPC classes we can track shifts over the pre-and post-crisis periods In Brussels, Berlin and Vienna

In the Brussels region we observe:

- a decrease in the RTA index in the IPC classes: “Fertilisers; organic chemistry”, “Organic macromolecular compounds”, “Computing; calculating”, “Physical and chemical processes and apparatus”, “Measuring; testing” and “agriculture”.
- an increase in the RTA index in the IPC classes: “Electric communication technique”, “Working of plastics” and “Basic electric elements”.

Therefore, more IPC classes indicate a decrease in RTA indexes in the post–crisis period than an increase.

Regarding the Berlin region we found:

- a decrease in the RTA index in the IPC classes: “Basic electric elements”, “Measuring; testing”, “Agriculture”, “Physical and chemical processes and apparatus”, “Fertilisers; organic chemistry” and “Milling; cleaning; disposal of solid waste”.
- an increase in the RTA index in the IPC classes: “Computing; calculating”, “Electric communication technique” and “Biochemistry; sugar”.

As in the Brussels-Capital Region, the Berlin region reveals an RTA index in most IPC classes that decreases in the post–crisis period.

The Vienna region shows:

- a decrease in the RTA index in the IPC classes: “Computing; calculating”, “Electric communication technique”, “Basic electric elements”, “Generation, conversion”.
- an increase in the RTA index in the IPC classes: “Agriculture”, “Biochemistry; sugar”, “Fertilisers; organic chemistry”, “Measuring; testing”, “Physical and chemical processes and apparatus”.

In the Vienna city region, we notice an increase of RTA indexes in 5 out of 10 IPC classes during the post–crisis period.

## 2.6 Scientific publication output: key features and trends

Bibliometrics is a tool by which the state of science and technology can be observed through the overall production of scientific literature, at a given level of specialisation (Okubo, 1997). Norton defined bibliometrics as the measurement of texts and information (Norton, 2000). Nowadays, bibliometrics is considered a helpful tool to understand the past and potentially to forecast the future. If patents are the main indicator of innovative output in industry, publications can be a good indicator of scientific effectiveness in the higher education system (Patel and Pavitt, 1995). Scientific indicators based on scientific publications can assess the current state of science and can be used in decision-making and research management. It is worth mentioning that bibliometric indicators are more effective and useful at higher levels of aggregation (a large set e.g. a country, city, and university), but can be limited in analysing individuals or small research teams.

The aim of this chapter is to provide basic information about bibliometric data, construction of indicators based on scientific publications, as well as guidelines for the compilation and interpretation of scientific publication indicators.

### 2.6.1 SCOPUS: data and method

Bibliometric analysis is an instrument for extracting necessary information from different databases. There are various bibliometric bases made to track the results of science and technology activity (PubMed, Scopus, Web of Science, Google Scholar and etc.) For researchers who perform bibliometric analyses, the existence of these different databases raises the question of the comparability and stability of statistics obtained from these sources. In our research the SCOPUS database is used as a data source. It has 66 million records covering over 22,000 peer-reviewed journals, 500 book serials and accounts for 34,000 individual book volumes and more than 138,000 non-serial books and others. The main criteria for choosing this database are:

- Scopus is the largest abstract and citation database of peer-reviewed literature: scientific journals, books and conference proceedings—tracking of scientific publications starting from 1858.
- Scopus offers about 20% more coverage in terms of citation analysis than Web of Science (Falagas et al., 2008).
- Moreover, Scopus covers most scientific fields.
- Scopus database indexes substantially more journals than other databases.
- PubMed, Google Scholar, and Web of Science are established by the United States, while Scopus comes from Europe.

Scopus has emerged as a reliable and easy to use research tool for bibliometric analysis. However, Scopus did not yet break the monopoly of its competitor. Several studies have examined and compared the coverage of Scopus and WOS in different disciplines. Falagas, et al. (2008) compared the strengths and weaknesses of WOS and Scopus for retrieving information. The authors found that Scopus listed 20% more articles than WOS since Scopus included a more “expanded spectrum of journals.” Bakkalbasi, et al., 2006 examined Scopus and WOS for citing articles, where they concluded that all of these databases would not stand alone as a comprehensive resource for citing articles. The process of citation is a complex procedure, and that it certainly does not provide an “ideal” monitor on scientific performance. The natural and health sciences are typically well covered in WOS and some specific disciplines which are often leading to better citation counts. In addition, Scopus database indexes substantially more journals than other databases and covers most scientific fields.

The data used in this research concern scientific publication statistics with at least one author from Brussels, Berlin and Vienna from 1993 to 2013 based on at least one author’s address in these cities. In our research, we focused on comparison at three different spatial levels: regional, city agglomerations and the nearest capital cities of the metropolitan regions (see Chapter 2.3-2.3.1).

## 2.6.2 Methodology

Bibliometrics has been defined as “the application of statistical and mathematical methods to books and other media of communication” and can be applied to the study of scientific research (Pritchard, 1969). The number of publications provides a crude approximation of the measure of the level of peer-reviewed scientific production within countries (Compendium of Bibliometric Science Indicators, 2016).

In this analysis, we used the Scopus data base, which gives a comprehensive overview of the world's research output in the fields of science, technology, medicine, social sciences, and arts and humanities. Publication and patent data together can provide a reliable picture of the varied nature of scientific and technological change and innovation. Moreover, publication and patent data can provide some further indication of R&D activities in the field and the position and specialisation of countries and regions. The main benefit of these indicators is the unique empirical characterization they provide of the way actors interact as a collective system of knowledge production and diffusion (OECD, 1996). However, publications and patents suffer from similar limitations.

Thousands of articles are published daily in scientific journals, with millions of citations in these publications, and provide a paper trail of the development, structural relationships, and diffusion of scientific knowledge. Publications and their citations are used as indicators for the performance of the public research system of countries and cities, or specific universities and institutes (Palmberg et al., 2009).

As patent-based indicators, publication data have their own advantages and disadvantages (Palmberg et al., 2009).

Advantages:

- Publications are closely linked to research activity
- All publications have a quality control
- Coverage of a broad range of scientific disciplines
- Data are available over long time series
- Publicly available at a low cost

Disadvantages:

- Publication databases are biased in favour of English-language journals as the mainstream outlets
- Combinations of different journal-specific databases make targeted searches cumbersome
- They only cover the codified aspects of scientific research
- Citation data may not only reflect genuine interrelationships and quality of research
- Publication behaviour and propensities may vary significantly across disciplinary fields

This research presents the results of investigating the research and publishing activities of authors and to what extent new approaches can be used to collect statistical data on scientist behaviour and impact. It does not aim to provide a comprehensive exploration of the full potential of bibliometric data.

To collect data from Scopus, we developed a few important methodologies to obtain reliable and explicit data. The search procedure includes: in advanced search in the Scopus web-site we chose the option of "affcity" and searched Brussels city, using 3 different spelling of Brussels city, such as "Brussels", "Brussel" and "Bruxelles". The total number of observations collected is somewhat higher than the Scopus summary suggested (82,192 observations as opposed to 76.630 observations from the Scopus summary). In the next step, we reduced the duplicated observations from the database, which reduced our sample to 76,439 observations. We also used counting schemes, according to which publications must be assigned to the contributing units. The fractional counting scheme, that is, if n units (authors, institutions, countries, etc.) have contributed to the paper in question, each contributing unit takes the value 1/n for this paper (for instance, applied by CHI Research Inc., Haddon Heights, NJ, USA)( Glanzel, 2003). All our next steps were directed to cleaning and harmonising data.

Then, we identified countries for every scientific publication and its affiliation. Nearly 5 % of countries were not detected due to spelling mistakes or completely missing data. Additionally, we found and cleaned all possible cities of Belgium in our sample. All cities were assigned to one of the 43 Belgian districts by NUTS 3 level (EUROSTAT), regions and city agglomerations. 4 % of cities were not identified and cannot be assigned to the district or region level. The following step was focused on identifying universities, organisations, companies and institutions. Indeed, since many institutions have various spellings (institutions may appear with different names and abbreviations) in the same data set, it is necessary to clean the names/abbreviations and unify in a "standardized" way. Manually, we developed the list with all possible variations of names of universities, organisations, companies and institutions to match the same organisations' names. However, this part of the raw data set contains 25% of observations which are not possible to recognise.

The main issue of this raw data concerns spelling mistakes (using different languages, abbreviations, written mistakes), which makes the process of identifying cities and organisations slow and unclear.

The cleaning process of data for Vienna (or Wien, as a spelling difference) was more time-consuming as we found many spelling mistakes or missing values. To reduce this problem, we developed an additional search with countries and names of different organisations. We were not able to detect 83,008 observations out of 250,409. Using specific manipulations, we reduce the number of unidentified observations to 72,466, which is 28.9%.

We faced similar difficulties in cleaning the Scopus data for Berlin (Berlin does not have different spellings). As we found many unidentified observations in the raw database, we implemented similar methods to solve the same issue. At first, we could not identify 124,936 observations out of 405,823. After the cleaning procedure, we reduced this number to 93,457 observations, which is 23%.

### 2.6.3 Number of scientific publications with at least one author from Brussels

Scientific publication counts provide a primary, simplistic and approximate measure of the quantity of work produced by a scientist. They can provide the research dynamics of a given country, city, university or other organisation over time. Publication counts are considerable indicators of research activity, especially of investment in "doing basic science" which can be interpreted as formatting absorptive capacity (Gambardella, 1992).

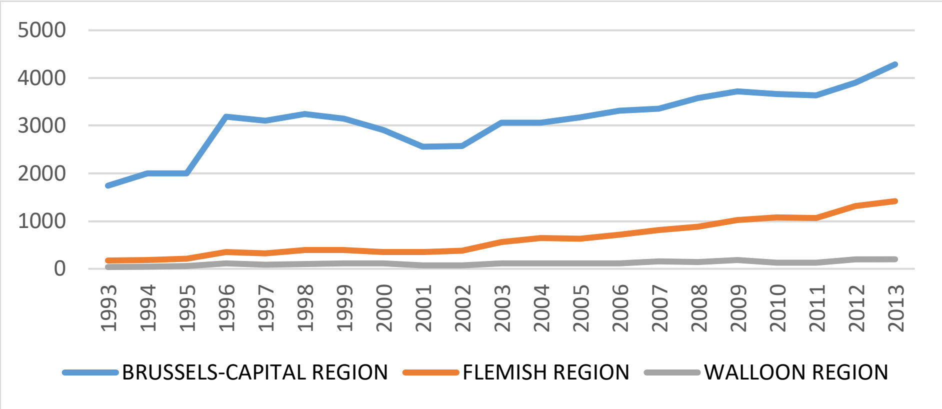
Figure II-17 illustrates the growth in the number of scientific publications over time across the main Belgian regions. For this indicator, scientific publication counts were used (see methodology Section 5.3). Like patent counts, publication counts can provide a measure of invention and scientific output. Counting publications provides a very partial picture of a country/city/city agglomeration's contribution to a scientific field, as simple counts give no indication of the quality of publications (Compendium of Bibliometric Science Indicators, 2016).

Considering the regional level, the Brussels-Capital Region reveals higher performance than Flanders and Wallonia for the period 1993-2013, due to the analysis based on scientific publications with authors located in Brussels. The Flemish Region's performance over time is higher than that of Wallonia. All Belgian regions present a constant growth of scientific publications over time. The pre-crisis (2000-2008) and post-crisis (2009-2013) periods show constant growth in the number of publications in all regions[19]. During the 1995-1998 period, The Brussels-Capital Region shows quite rapid growth in the number of scientific publications. In addition, in the post-crisis period, we can observe a slight decrease in the number of publications in a 1-1.5-year period, with subsequent growth. This decrease may be explained by the influence of the economic crisis and the fact that R&D expenditure in the Brussels-Capital Region for most sectors is lower than in the pre-crisis period (2000-2008) (see Chapter 2.2, A. Spithoven[20]).

[19] To investigate the impact of the economic crisis of 2008 on patenting activity, the period from 1993 to 2013 is split into two sub periods: a pre-crisis sub-period (1993-2008) and a post-crisis one (2009-2013).

[20] A. Spithoven, 2016 "Regional R&D growth: positioning the Brussels-Capital Region", joint work carried out within the Innoviris and BRUSTI project.

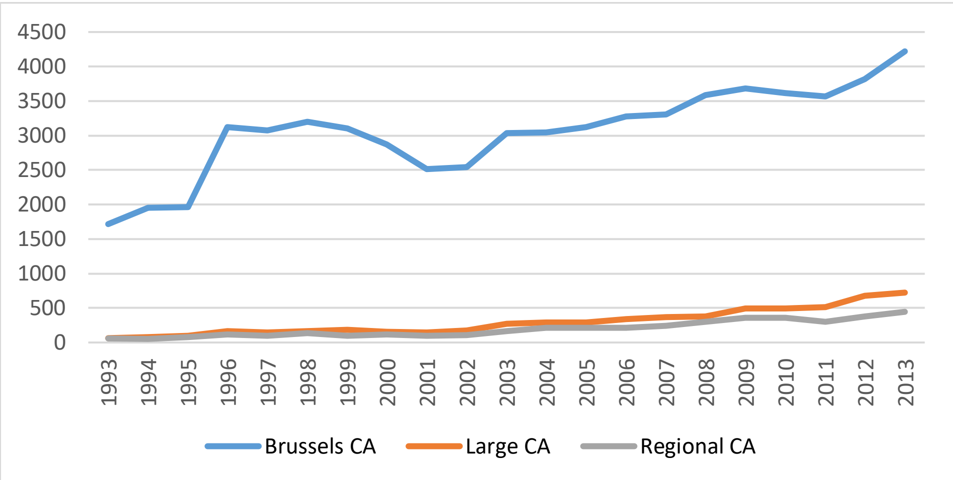
**Figure II-17. Number of scientific publications with at least one inventor from Brussels: Evolution over the period 1993-2013– Brussels-Capital Region compared to the other two Belgian regions**




Source: own calculations, Scopus

Further insights are provided by Figure II-18 which is performed at the level of the Brussels city agglomeration (CA) in comparison with large and regional city agglomerations in Belgium. This indicator is based on the scientific publication count methodology (see Section 2.5.3.). According to the results, Large CAs show a slightly higher performance in terms of the number of scientific publications than Regional CAs. This evidence can be explained by universities being more concentrated in that area. The total performance of Large CAs and Regional CAs is much lower than Brussels CA, as initially the bibliometric analysis is based on authors located in Brussels. The post-crisis period shows a slight decline in the number of publications in 2009-2011 and subsequent growth in all CAs.

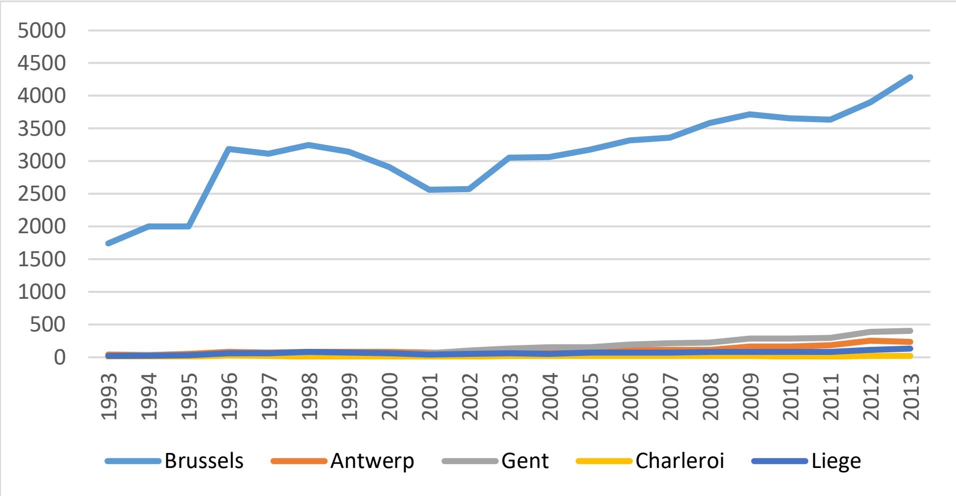
**Figure II-18. Number of scientific publications with at least one inventor from Brussels: Evolution over the period 1993-2013 - Brussels city agglomeration (CA), 4 large city agglomerations (Antwerp, Liege, Gent and Charleroi), and 13 regional city agglomerations**




Source: own calculations, Scopus

Figure II-19 illustrates the number of scientific publications at a more diversified spatial level. This indicator is based on scientific publication count methodology to compare innovation output for different spatial dimensions of scientific publication data with at least one author from Brussels.

**Figure II-19. Number of scientific publications with at least one inventor from Brussels region: Evolution over the period 1993-2013 of Brussels region, and 4 metropolitan regions (Antwerp, Liege, Gent and Charleroi)**




Source: own calculations, Scopus

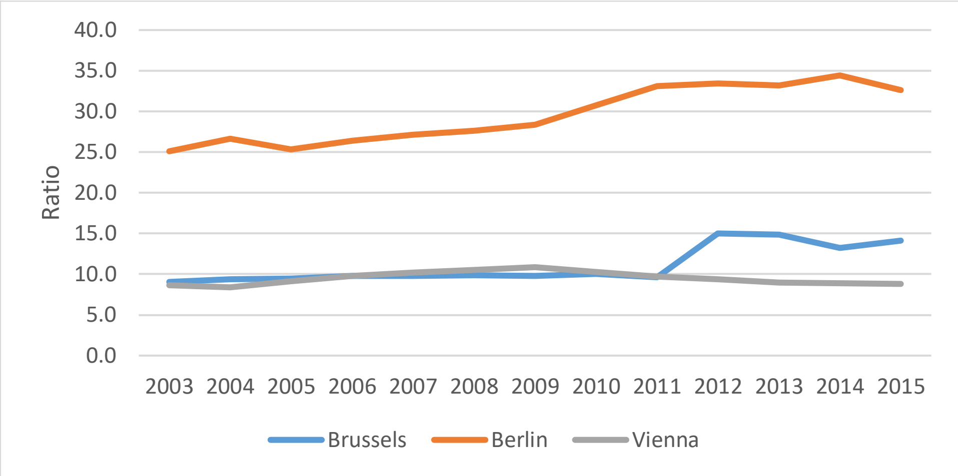
Gent and Antwerp show a higher performance than the other two metropolitan regions. The total performance of the 4 metropolitan regions is significantly lower than that of Brussels. Gent presents the highest number of scientific publications in 2013. Antwerp has the highest number of scientific publications in 2012, but this number decreases thereafter. Charleroi's performance is the lowest of the metropolitan regions.

Next, we compare the ratio[21] of scientific publications with at least one author from Brussels, Berlin and Vienna per 10,000 inhabitants. The methodology of this indicator, presented in Figure II-20, is like the previous indicators for patents (see Figure II-10). In Figure II-21, we calculate the indicator in relative terms where we use the population of the capital city regions (Brussels, Berlin and Vienna are considered as mainly relevant at the spatial level of NUTS2) for the period 1993-2013. In this indicator, the number of scientific publications is divided by the population of the Brussels-Capital, Berlin and Vienna regions per 10,000 inhabitants, to obtain a relative ratio. Three regions are compared. The Brussels-Capital Region has a higher scientific publication performance than the Berlin and Vienna regions with regard to the population concentration in these cities. The Vienna region reveals better scientific output than the Berlin region. All the regions considered show constant growth in the number of scientific publications divided by the population. This tendency can be partially explained by the number of universities and research centres producing scientific publications in the city regions. To make a comparable link between the ratio of scientific publications and the number of universities and research centres of metropolitan cities, we calculated the ratio between the number of researchers in the public sector and population (Eurostat, 2003-2015). The results obtained show that Berlin has the highest ratio. Brussels performs better then Vienna in most

21 Ratio = Number of publications / population

of the period (see Figure II-21). Furthermore, some similar tendencies are seen in terms of ratio distribution.

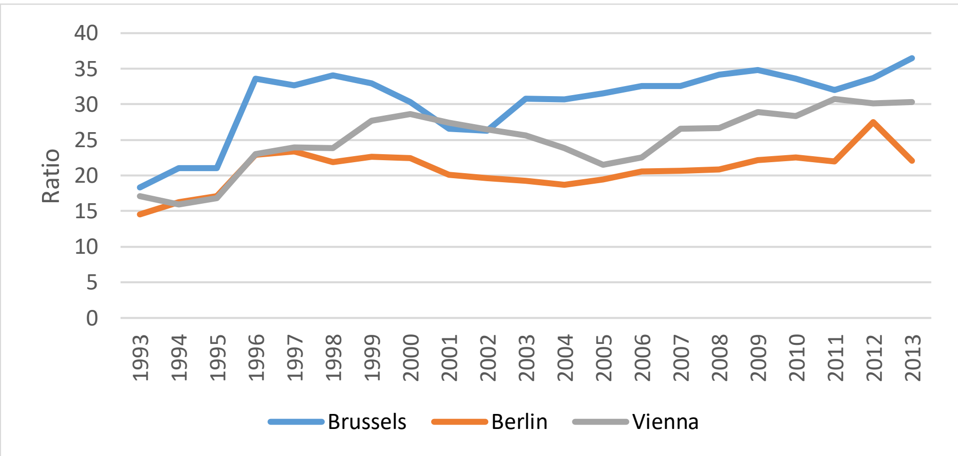
**Figure II-20. Ratio of researchers per 10,000 inhabitants in the public sector from Brussels, Berlin and Vienna, 2003-2015**




Source:Eurostat.

During the post-crisis period, there is a slight decrease in all regions. In the pre-crisis period the Vienna region shows a considerably lower ratio than in the post-crisis period. Brussels has the highest scientific publication performance. The highest number of scientific publications corresponds to Brussels in 2013, Berlin in 2011 and Vienna in 2012.

**Figure II-21. Ratio of scientific publications per 10,000 inhabitants with at least one inventor from Brussels, Berlin and Vienna: Comparison of Brussels with Berlin and Vienna**




**Source: own calculations, Scopus**

## 2.6.4 Share of scientific publications by organisation (company, government non-profit organisation, university)

Higher education institutions are historically motivated to publish scientific papers rather than patents. Yet, as mentioned in the work of Etzkowitz et al. (1998), “today, universities are undergoing a second revolution”, which is leading them increasingly to translate “research findings into intellectual property, a marketable commodity, and economic development". Around 66% of scientific publications come from academic institutions, Research and Technology Organisations (RTOs) and government agencies. Only 7% of all scientific publications come from companies (own calculations made for 1990-2015 period).

Figure II-22 analyses the distribution of scientific publication shares according to the type of organisation[22]. To produce this indicator, the number of scientific publications for each sector for every region was divided by the total number of scientific publications with at least one author from Brussels for the 1993-2013 period and the results are expressed as a percentage. The original data set does not contain the type of organisation in the patent database. Thus, an additional parameter is defined to identify the type of organisation. We used Bel-First data source to extract these data for different organisations. Bel-first[23] contains comprehensive information on companies in Belgium and Luxembourg[24]. This source is used to research individual companies, search for companies with specific profiles and for analysis.

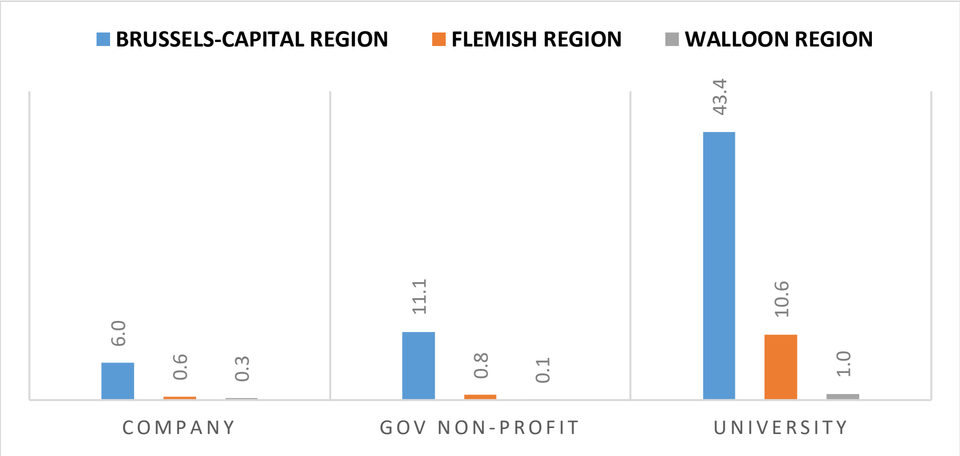
The "University" sector has the highest performance, based on the share of scientific publications for all three regions. "Government non-profit organisations" produce less than the "University" sector. "Companies" have the lowest performance in all regions. In all sectors, the Brussels-Capital Region has the highest number of scientific publications. The Flemish and Walloon regions have much lower shares than the Brussels region. The Walloon Region reveals the lowest shares in all sectors. This distribution of scientific publications by type of organisation indicates that universities tend to produce more scientific publications than companies.

[22] Company, Government non-profit organisations and universities

[23] Bureau van Dijk

[24]The main information of Bel-first Finance contains:
Company financial information in detailed format (full Balance sheet, Income statement) with up to 10 years of history
Financial strength ratios
Social balance sheet
Current and Previous Board Members
Original filings/images as filed at the National Bank of Belgium
Auditor's report
Stock data for listed companies
Detailed corporate structures and the corporate family
Shareholders and subsidiaries
Legal information i.e. National Social Security Office (NSSO) summons, outstanding and regularised protests and judgments.
M&A deals and rumours.

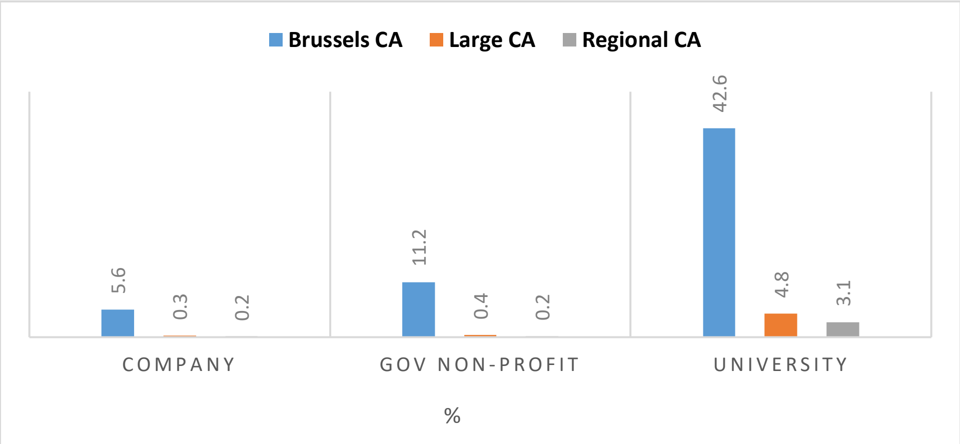
**Figure II-22. Share in % of scientific publications by organisation (company, government non-profit organisation, university) with at least one author from Brussels (1993-2013) compared to the other two Belgian regions**




Source: own calculations, Scopus
Note: Unknown observations are not mentioned in the Figure

The next indicator reflects the share of scientific publications by organisations, comparing city agglomeration levels.

**Figure II-23. Share in % of scientific publications by organisation (company, government non-profit organisation, university) with at least one author from Brussels (1993-2013) compared to the other two Belgian regions**




Source: own calculations, Scopus
Note: Unknown observations are not mentioned in the Figure

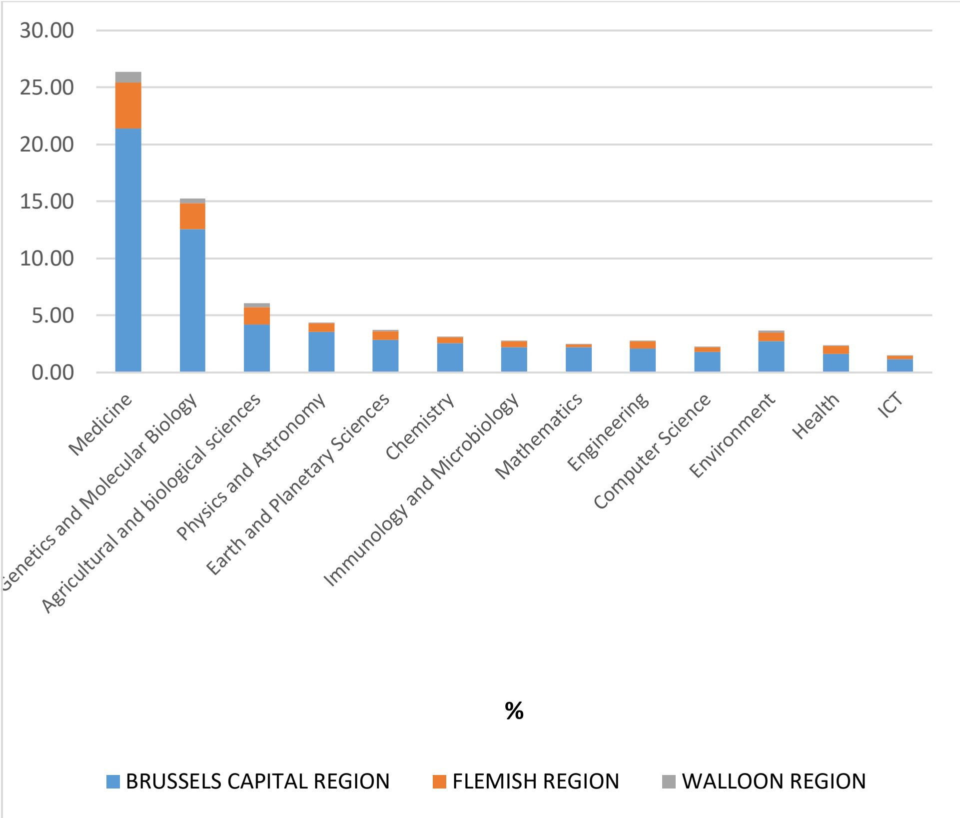
For this indicator we use the same methodology as in Figure II-23. As expected, the shares of scientific publications by organisations are highest in the Brussels CA. The “University” sector is one of the most representative of the other sectors, whilst the “Company” sector is the smallest. The shares of scientific publications by organisations in Large CAs and Regional CAs differ slightly, and the Regional CA has the lowest shares of all city agglomerations.

### 2.6.5 Relative share of top scientific fields

The dynamics and evolution of scientific fields is a crucial element in the study of bibliometric indicators. Continuing our research, we focused on identifying the scientific fields of scientific publications, as Scopus raw data does not provide this. This information can be retrieved from the raw data source in the "Source title" of the publication. Initial data is matched with a list of journals, where every journal is assigned to a scientific field (source: Journal classifications, own treatments). Based on this methodology we construct this indicator. For the last three scientific areas (strategic action domains: Environment, ICT and Health) we use a different approach. This approach is based on the Journal list, as well as on a different way of classifying Scientific Fields, and taken from Science–Metrix data source. The classification by Science – Metrix was modelled on those of existing journal classifications (ISI, CHI, ERA), and their groupings of journals acted as "seeds" or attractors for journals in the new classification. The scientific publication output captured by Scopus is distributed unevenly across 26 different fields in the All Science Journal Classification. As stated in the Compendium of Bibliometric Science Indicators, 2016 for the 2003-2012 period, Medicine accounted for the largest number of indexed documents, namely 4.4 million documents (24%), followed by Engineering (12%) and Biochemistry, Genetics & Molecular Biology (11%).

Figure II-24 provides some evidence about the distribution of relative shares of scientific fields among Belgian regions. The major scientific fields among regions are Medicine, Biochemistry and Agricultural and biological science. The Brussels-Capital Region has a larger share than the other two regions. As expected, the Walloon Region has a lower distribution of scientific publications in scientific fields than the Flemish region. The distribution of scientific publications among the strategic action domains of "Environment", "ICT" and "Health" reveals that "Environment" has a greater distribution than the other domains, with the Brussels region being dominant and the Walloon region at the other extreme. The "ICT" scientific field has the lowest share.

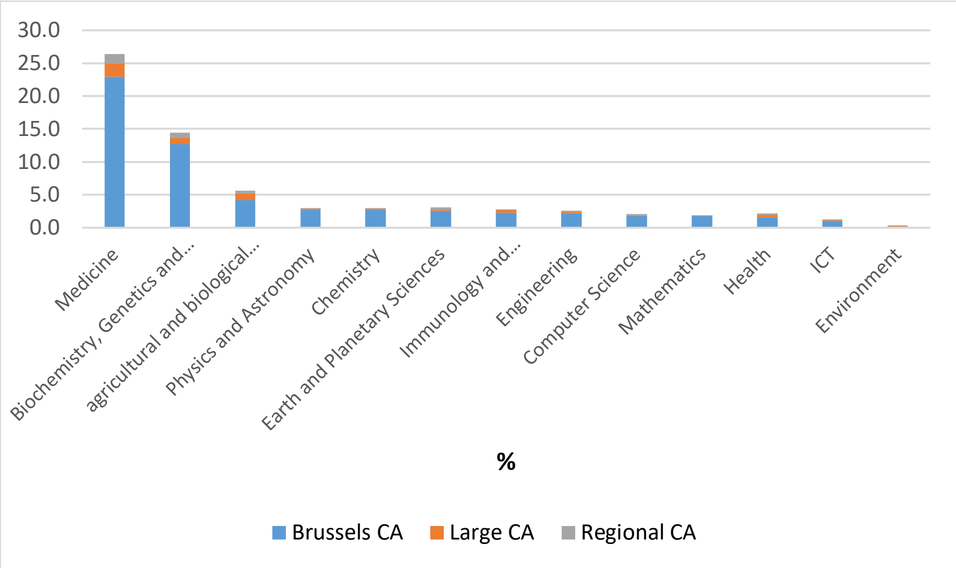
**Figure II-24. Relative share in % of top 10 scientific fields (1993-2013): compared to the other two Belgian regions**




Source: own calculations, Scopus

A comparison at the city agglomeration level reveals that the top scientific fields are "Medicine", "Biochemistry" and "Agricultural and Biological science". The Brussels CA has the highest shares among the top 10 scientific fields. However, the performance of Large CAs and Regional CAs is comparatively low. Overall, the shares of top scientific fields of Large CAs are slightly higher than in Regional CAs. We observed this tendency in all other indicators where we compare the city agglomeration level. The distribution of scientific publications among strategic action domains indicates that "Health" is more present in Brussels CA than the other city agglomerations. The "ICT" and "Environment" scientific fields show rather small shares.

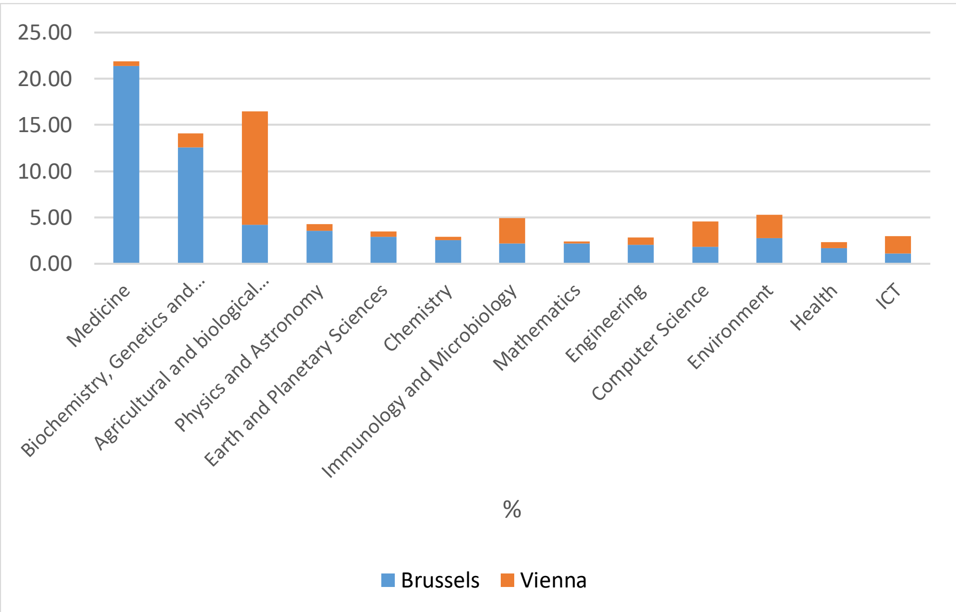
**Figure II-25. Relative share in % of top scientific fields (1993-2013): compared with metropolitan regions of Belgium (case of 4 large city agglomerations (Antwerp, Liege, Gent and Charleroi), and 13 other regional city agglomerations aggregated in one class**




Source: own calculations, Scopus

Based on the methodology of the two previous sections 24 and 25, we compare the relative shares of top scientific fields with at least one inventor from Brussels and Vienna city regions. The main limitation we face in this section lies in the Berlin raw data from Scopus, which contains missing records in the "Source title" of the publication to identify scientific fields.

**Figure II-26. Relative share in % of top scientific fields (1993-2013): Comparison of Brussels with Vienna**




Source: own calculations, Scopus

The results for this indicator are presented in Figure II-26. The Brussels-Capital Region has the highest share of scientific publications in "Medicine", "Biochemistry", "Physics and astronomy”, “Earth and planetary Sciences”, “Chemistry”, “Mathematics” and “Engineering”, while the Vienna region is better represented in “Agricultural and biological sciences”, “Immunology and Microbiology” and “Computer Science”. Regarding the distribution of scientific publications among strategic action domains, Vienna dominates in the “Environment” and “ICT” scientific fields, while Brussels has a slightly bigger share of scientific publications in the “Health” strategic domain.

### 2.6.6 Scientifically Revealed Advantage (SRA)

A scientifically revealed advantage (SRA) index provides an indication of a given economy's relative specialisation in various scientific fields. The methodology for constructing this indicator is based on the same technique we used to build the RTA index for patent data (see Section 5.10). Table II-9 provides some evidence of the SRA index for Belgian regions.

The Brussels-Capital Region appears to have a scientific advantage in some scientific fields (presented in descending order with the highest share of scientific publications): “Biochemistry, genetics and molecular biology - 1.04”, “Physics and Astronomy - 1.12”, “Chemistry – 1.03”, “Mathematics – 1.17”, “Computer Science – 1.03”. In the Flemish Region, the top 3 scientific fields with the corresponding SRA indexes indicate scientific advantage only in one field “Agricultural and “Biological sciences - 1.41”. For the Walloon Region, the SRA index indicates the following: “Medicine – 1.22”, “Agricultural and biological sciences – 1.81” and “Biochemistry, genetics and molecular biology – 0.88”. “Medicine – 1.22” and “Agricultural and biological sciences – 1.81” IPC indexes have a scientific advantage. With regard to strategic domains, only the Flemish region presents a scientifically revealed advantage in all fields over the other regions.

**Table II-9. Scientifically Revealed Advantage (SRA) in selected fields with at least one author from Brussels: Comparison of the Brussels-Capital Region with two other Belgian regions**

| Scientific field | Brussels-Capital Region | Scientific field | Flemish Region | Scientific field | Walloon Region |
|---|---|---|---|---|---|
| Medicine | 0.98 | Medicine | 0.92 | Medicine | 1.22 |
| Biochemistry, Genetics and Molecular Biology | 1.04 | Biochemistry, Genetics and Molecular Biology | 0.90 | Agricultural and biological sciences | 1.81 |
| Agricultural and biological sciences | 0.88 | Agricultural and biological sciences | 1.41 | Biochemistry, Genetics and Molecular Biology | 0.88 |
| Physics and Astronomy | 1.12 | Earth and Planetary Sciences | 1.02 | Earth and Planetary Sciences | 1.05 |
| Earth and Planetary Sciences | 0.98 | Physics and Astronomy | 0.83 | Chemistry | 1.20 |
| Chemistry | 1.03 | Engineering | 1.21 | Immunology and Microbiology | 1.16 |
| Engineering | 0.97 | Chemistry | 0.99 | Chemical Engineering | 1.41 |
| Mathematics | 1.17 | Immunology and Microbiology | 1.06 | Art and humanities | 0.75 |
| Computer Science | 1.03 | Computer Science | 1.09 | Engineering | 0.60 |
| Immunology and Microbiology | 0.98 | Environmental Science | 1.56 | Physics and Astronomy | 0.37 |
| **Environment** | *0.96* | **Environment** | *1.14* | **Environment** | *0.99* |
| **Health** | *0.86* | **Health** | *1.62* | **Health** | *0.40* |
| **ICT** | *0.96* | **ICT** | *1.29* | **ICT** | *0.96* |

Source: own calculations, Scopus

A comparison of SRA indexes between city agglomerations shows the scientific advantage of Brussels CA in the following scientific fields; “Medical and veterinary science; life-saving - 1.00”, “Fertilisers; organic chemistry - 1.04”, “Physics and Astronomy - 1.05”, “Chemistry - 1.04”, “Mathematics -1.18”, “Computer Science - 1.05”, “Art and humanities - 1.03”. The distribution of the RTA indexes among the top 3 IPC classes in Large CAs is: “Medicine - 0.92”, “Agricultural and biological sciences - 1.88” and “Biochemistry, genetics and molecular biology - 0.79”, where only “Agricultural and biological sciences” IPC class indicates a strong scientifically revealed advantage. Regional CAs reveal the following distribution of SRA indexes among scientific fields: “Medicine - 1.00”, “Biochemistry, genetics and molecular biology - 0.96” and “Agricultural and biological sciences - 0.97”. Regional CAs indicate scientific advantage in 7 out of 13 scientific fields. With regard to strategic domains, Brussels and Regional CAs have a scientific advantage in scientific fields, whilst Large CAs do not indicate any.

**Table II-10. Scientifically Revealed Advantage (SRA) in selected fields with at least one author from Brussels: Comparison of Brussels with metropolitan regions of Belgium (case of 4 large city agglomerations (Antwerp, Liege, Gent and Charleroi), and 13 other regional city agglomerations aggregated in one class**

| Scientific field | Brussels CA | Scientific field | Large CA | Scientific field | Regional CA |
|---|---|---|---|---|---|
| Medicine | 1.00 | Medicine | 0.92 | Medicine | 1.00 |
| Biochemistry, Genetics and Molecular Biology | 1.04 | Agricultural and biological sciences | 1.88 | Biochemistry, Genetics and Molecular Biology | 0.96 |
| Agricultural and biological sciences | 0.87 | Biochemistry, Genetics and Molecular Biology | 0.79 | Agricultural and biological sciences | 0.97 |
| Physics and Astronomy | 1.05 | Physics and Astronomy | 1.17 | Earth and Planetary Sciences | 1.23 |
| Earth and Planetary Sciences | 0.90 | Engineering | 1.30 | Engineering | 1.24 |
| Chemistry | 1.04 | Immunology and Microbiology | 1.52 | Computer Science | 1.46 |
| Engineering | 0.97 | Chemistry | 1.00 | Chemistry | 0.85 |
| Mathematics | 1.18 | Environmental Science | 1.73 | Economics, Econometrics and Finance | 1.75 |
| Computer Science | 1.05 | Art and humanities | 1.01 | Business, Management and Accounting | 1.73 |
| Art and humanities | 1.03 | Earth and Planetary Sciences | 0.56 | Art and humanities | 0.92 |
| **Environment** | *1.37* | **Environment** | *0.95* | **Environment** | *0.95* |
| **Health** | *0.58* | **Health** | *0.87* | **Health** | *2.06* |
| **ICT** | *0.79* | **ICT** | *0.99* | **ICT** | *1.06* |

Source: own calculations, Scopus

In Table II-11 we present the SRA index comparing the two city regions of Brussels and Vienna. The main limitation of this research is missing records in the “Source title” of the publication, which prevents us from identifying scientific fields.

**Table II-11. Scientifically Revealed Advantage (SRA) in selected fields with at least one author from Brussels: Comparison of Brussels with Vienna**

| Scientific field | Brussels | Scientific field | Vienna |
|---|---|---|---|
| Medicine | 0.98 | Medicine | 0.96 |
| Biochemistry, Genetics and Molecular Biology | 1.03 | Biochemistry, Genetics and Molecular Biology | 1.01 |
| Agricultural and biological sciences | 0.88 | Agricultural and biological sciences | 1.02 |
| Physics and Astronomy | 1.10 | Chemistry | 1.05 |
| Earth and Planetary Sciences | 0.98 | Physics and Astronomy | 1.08 |
| Chemistry | 1.04 | Engineering | 1.00 |
| Engineering | 0.96 | Earth and Planetary Sciences | 0.98 |
| Mathematics | 1.18 | Computer Science | 1.02 |
| Art and humanities | 1.01 | Mathematics | 1.07 |
| Computer Science | 1.03 | Immunology and Microbiology | 1.00 |

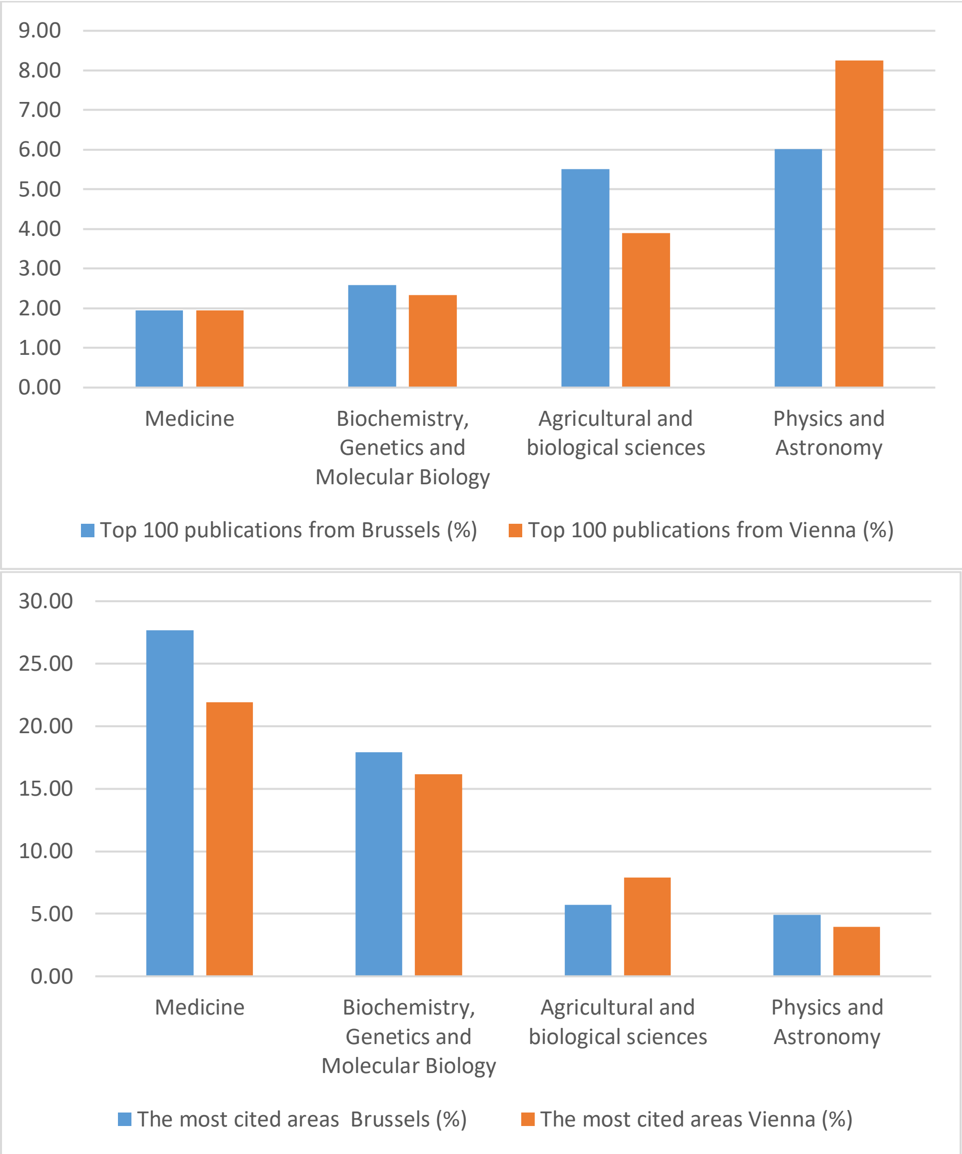
Source: own calculations, Scopus

Regarding the top 10 IPC classes in Brussels, we can see scientific advantage in such fields as "Biochemistry, Genetics and Molecular Biology", "Physics and Astronomy", "Chemistry", "Mathematics" and "Computer Science". Vienna has a scientifically revealed advantage in the following scientific fields: "Biochemistry, Genetics and Molecular Biology", "Agricultural and biological sciences", "Chemistry", "Physics and Astronomy", "Computer Science" and "Mathematics". In conclusion, Brussels applies relatively more patents in more fields than Vienna. Similar trends are observed between the regions considered in terms of SRA index distribution.

### 2.6.7 TOP 100 most cited scientific publications by scientific fields

Counting the most-cited publications in each country provides a quality-adjusted measure of research output, in other words, a proxy for scientific excellence (Bornmann et al., 2012). "The quality of a paper should be assessed as higher, the more frequently a paper is cited" (Bornmann et al., 2012). To construct this indicator, we counted the number of citations by scientific sectors for Brussels and Vienna. Then we focused on the 4 leading sectors in common. In each scientific field, we chose the top 100 cited articles and calculated the percentage to provide the comparison.

**Figure II-27. Top 100 most cited scientific publications by scientific fields: Comparison of Brussels with Vienna**



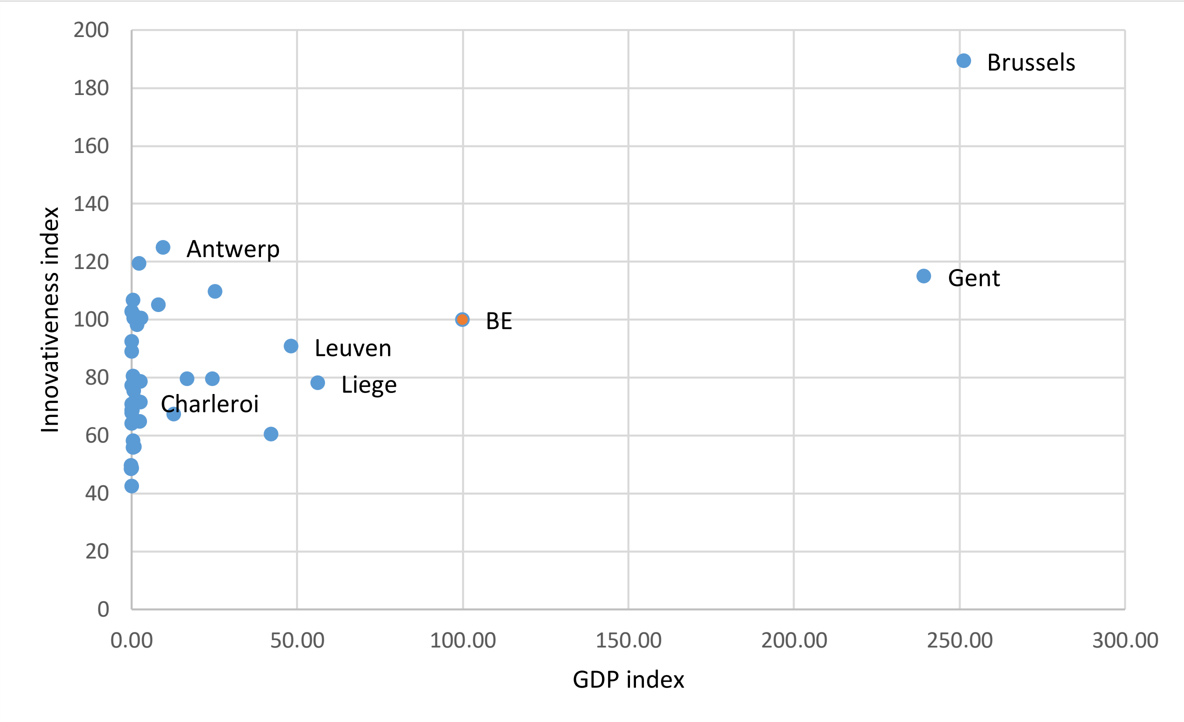

Source: own calculations, Scopus

In the Brussels-Capital Region the most cited fields are "medicine", "biochemistry, genetics and molecular biology", "agricultural and biological sciences", "physics and astronomy" and "earth and planetary science". The most cited scientific fields in Vienna are "medicine", "biochemistry, genetics and molecular biology", "agricultural and biological sciences", "physics and astronomy" and "chemistry". "Medicine" is the most cited research field in both cities, whilst the level of citation is higher in Brussels and cited equally in the top 100 publications between Brussels and Vienna. For "biochemistry, genetics and molecular biology", we observe similar tendencies in the most cited areas and top 100 publications, where Brussels has a slightly higher share of citations. "Agricultural and biological sciences" is cited more in Vienna than in Brussels, but in the top-100 publications the citation share is higher in Brussels. The opposite results are observed in the field of "physics and astronomy". Overall, we can assume that Brussels generates quality publications slightly above those of Vienna.

## 2.6.8 Concentration of innovativeness and wealth at the district level

Construction of this indicator uses the same methodology as in Section 5.8. Figure II-28 shows the level of concentration of innovativeness of scientific publications in Belgian districts. It follows from these figures that Brussels has the highest Innovativeness index as well as GDP index. Antwerp indicates a higher value in the innovativeness index than Gent but has a very low GDP index. Gent shows a slightly lower GDP index than Brussels. Leuven, Liege and Charleroi are below the Belgian average. Three of these districts have a higher GDP index than Antwerp. Turnhout has higher indicators than Antwerp. Hence, districts with higher R&D intensity – gross domestic expenditure on R&D (GERD) as a percentage of GDP – also tend to show higher rates of scientific publications per capita.

**Figure II-28. Concentration of innovativeness and wealth at the district level (Brussels and metropolitan regions of Belgium) (Belgium = 100, average 1993-2013)**




Source: own calculations, Scopus

## 2.6.9 Scientific proximities within and across industries by Belgian districts

Technological proximities among districts give a picture of how scientific publications by scientific field are distributed and concentrated (Herfindahl index[25]) across geographic areas (Cincera M. and Capron H., 2003). The technique we used to construct this indicator is taken from Chapter 2.5.6.

[25] The Herfindahl-Hirschman index (HHI) is a commonly accepted measure of market concentration. It is calculated by squaring the market share of each firm competing in a market, and then summing the resulting numbers, and can range from close to zero to 10,000.

**Table II-12. Scientific proximities within and across industries by Belgian districts (1993-2013)**

| | Antwerp | Brussels | Charleroi | Gent | Liege | HHI |
|---|---|---|---|---|---|---|
| Antwerp | 1 | | | | | 0.12 |
| Brussels | 0.91 | 1 | | | | 0.12 |
| Charleroi | 0.82 | 0.91 | 1 | | | 0.36 |
| Gent | 0.89 | 0.93 | 0.81 | 1 | | 0.11 |
| Liege | 0.85 | 0.97 | 0.83 | 0.93 | 1 | 0.11 |

Source: own calculations, Scopus

| | Antwerp | Mechelen | Turnhout | Brussels | Leuven | Brugge | Kortrijk | Oostende | Gent | Sint-Niklaas | Charleroi | Mons | Doornik | Liege | Verviers | Namur | HHI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Antwerp | 1 | | | | | | | | | | | | | | | | 0.12 |
| Mechelen | 0.86 | 1 | | | | | | | | | | | | | | | 0.19 |
| Turnhout | 0.66 | 0.54 | 1 | | | | | | | | | | | | | | 0.12 |
| Brussels | 0.91 | 0.88 | 0.81 | 1 | | | | | | | | | | | | | 0.12 |
| Leuven | 0.89 | 0.87 | 0.81 | 0.99 | 1 | | | | | | | | | | | | 0.11 |
| Brugge | 0.81 | 0.91 | 0.54 | 0.90 | 0.87 | 1 | | | | | | | | | | | 0.27 |
| Kortrijk | 0.81 | 0.86 | 0.72 | 0.91 | 0.90 | 0.88 | 1 | | | | | | | | | | 0.15 |
| Oostende | 0.78 | 0.92 | 0.50 | 0.79 | 0.79 | 0.81 | 0.78 | 1 | | | | | | | | | 0.24 |
| Gent | 0.88 | 0.93 | 0.74 | 0.93 | 0.93 | 0.82 | 0.87 | 0.92 | 1 | | | | | | | | 0.11 |
| Sint-Niklaas | 0.68 | 0.78 | 0.35 | 0.75 | 0.71 | 0.87 | 0.73 | 0.68 | 0.67 | 1 | | | | | | | 0.31 |
| Charleroi | 0.82 | 0.90 | 0.55 | 0.91 | 0.88 | 0.99 | 0.88 | 0.78 | 0.81 | 0.88 | 1 | | | | | | 0.36 |
| Mons | 0.85 | 0.78 | 0.84 | 0.89 | 0.90 | 0.66 | 0.81 | 0.79 | 0.93 | 0.52 | 0.66 | 1 | | | | | 0.09 |
| Doornik | 0.81 | 0.91 | 0.53 | 0.89 | 0.86 | 0.99 | 0.88 | 0.79 | 0.81 | 0.89 | 0.99 | 0.66 | 1 | | | | 0.40 |
| Liege | 0.87 | 0.87 | 0.79 | 0.96 | 0.97 | 0.86 | 0.89 | 0.76 | 0.92 | 0.70 | 0.87 | 0.87 | 0.85 | 1 | | | 0.11 |
| Verviers | 0.76 | 0.76 | 0.55 | 0.84 | 0.86 | 0.82 | 0.78 | 0.66 | 0.76 | 0.74 | 0.83 | 0.72 | 0.81 | 0.87 | 1 | | 0.17 |
| Namur | 0.60 | 0.68 | 0.53 | 0.59 | 0.60 | 0.43 | 0.53 | 0.83 | 0.82 | 0.31 | 0.40 | 0.80 | 0.41 | 0.59 | 0.41 | 1 | 0.19 |

Source: own calculations, Scopus

The results of this indicator show that Brussels district has the highest scientific proximities with Leuven, Liege, Gent, Kortrijk, Charleroi, Doornik, Mons and Verviers. The lowest scientific proximities are observed for Oostende, Sint-Niklaas and Namur. Antwerp is scientifically close to Mechelen, Brussels, Leuven, Brugge, Gent, Mons, Liege and scientifically distant from Turnhout, Sint-Niklaas, Verviers and Namur. Gent shows high scientific proximities to Mechelen, Brussels, Leuven, Liege and Oostende. Charleroi district indicates close scientific relations with Mechelen, Brussels, Leuven, Brugge, Kortrijk, Gent and other districts. Hence, the highest HHI index reveals Brugge, Oostende, Sint-Niklaas, Charleroi and Doornik. These districts indicate a lower level of technological diversification. Looking at the off-diagonal cells, Table II-12 gives an idea of how scientifically distant the districts are.

## 2.6.10 Relative specialisation index among Belgian regions

The publication profile can be expressed by the Relative Specialisation Index (RSI). RSI indicates whether a country has a relatively higher or lower share of world publications in particular fields of science than its overall share in the world total of publications. The symmetric RSI is a relative indicator based on the Activity Index (AI). The Activity Index is defined as:

$$AI = \frac{the\ share\ of\ given\ field\ in\ the\ publications\ of\ the\ given\ country}{\text{the share of given field in the world total of publications}}$$

The RSI is defined as:

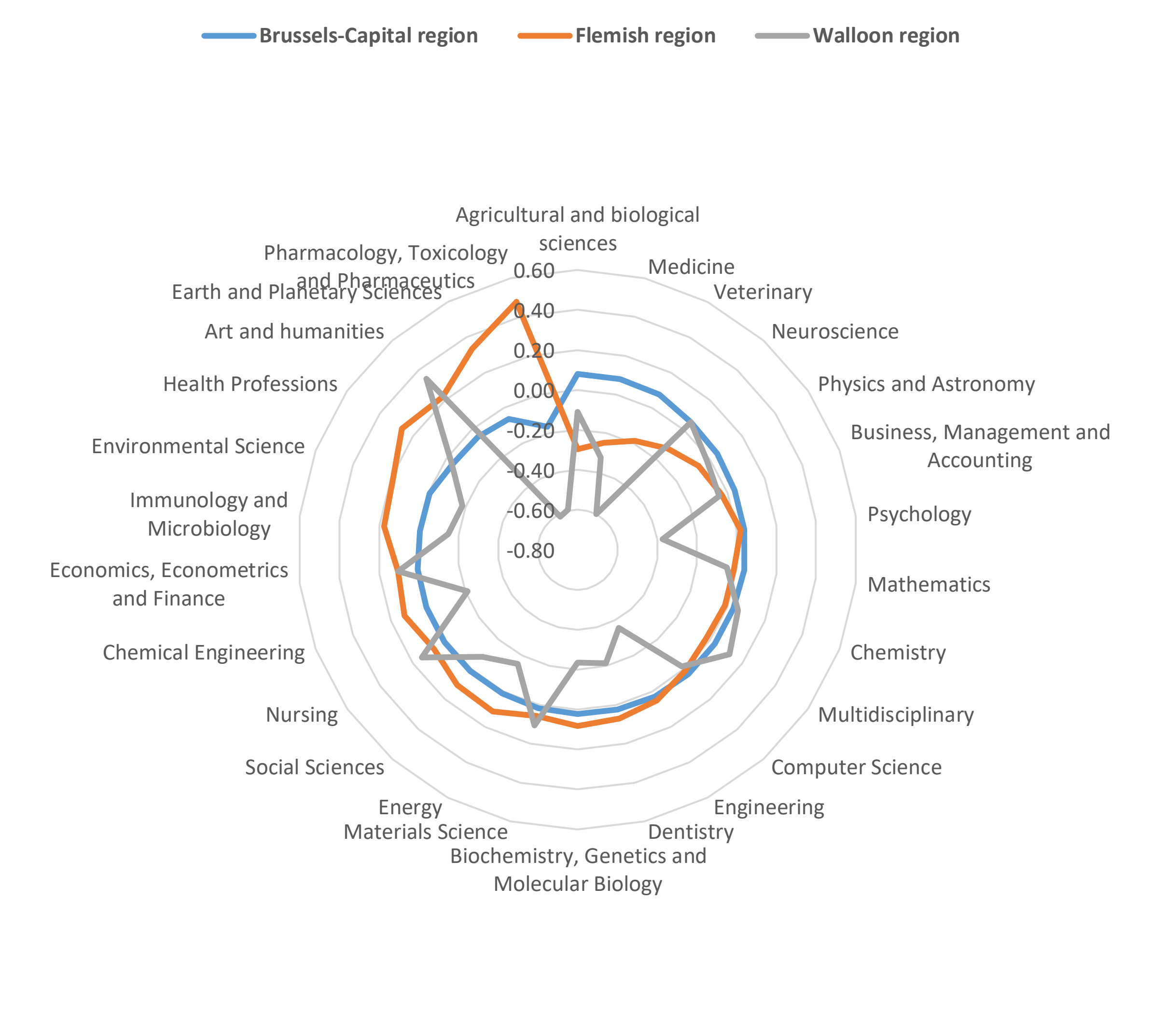
$$RSI = \frac{\mathrm{AI} - 1}{\mathrm{AI} + 1}$$

RSI takes its values in the range [-1, 1]. It indicates whether a country has higher than average activity in a scientific field (RSI >1) or lower than average activity (RSI <1). RSI = 0 reflects a completely balanced situation. It is important to note that RSI reflects a certain internal balance among the fields in the given country, i.e. positive RSI values must always be balanced by negative ones (no country can have its RSI values all positive or all negative). Furthermore, low values indicate homogenous distributions between the various research fields (Schneider, 2010).

Table II-13 shows that the Brussels-Capital Region has positive RSI values in Agricultural and biological sciences, Medicine, Veterinary, Neuroscience, Physics and Astronomy, Business, Management and Accounting, Psychology, Mathematics, Chemistry, Multidisciplinary, Computer Science, Engineering, Dentistry, Biochemistry, Genetics and Molecular Biology, Materials Science, Energy, Social Sciences, Nursing, Chemical Engineering, Economics, Econometrics and Finance. For the Flemish region the positive values are in Pharmacology, Toxicology and Pharmaceutics, Earth and Planetary Sciences, Health Professions, Art and humanities, Environmental Science, Immunology and Microbiology, Chemical Engineering, Energy, Social Sciences, Economics, Econometrics and Finance, Biochemistry, Genetics and Molecular Biology, Nursing, Dentistry, Materials Science, Engineering, Psychology, Computer Science. The Walloon region has a positive RSI index under that of other regions: Art and humanities, Nursing, Multidisciplinary, Materials Science, Economics, Econometrics and Finance, Chemistry and Neuroscience. The research of Glänzel (2000) identified four basic paradigmatic patterns in publication profiles based on the RSI index, these being:

Type 1: Western model, the characteristic pattern of developed Western countries with clinical medicine and biomedical research as dominating fields.
Type 2: Characteristic pattern of the former socialist countries, economies in transition and China, with excessive activity in chemistry and physics.
Type 3: Bioenvironmental model, which is the most typical pattern in developing and more natural-resource-oriented countries (e.g. Australia, or South Africa), focusing mainly on biology and earth and space sciences.
And Type 4: Japanese model, now also typical for other developed Asian economies, where engineering and chemistry are predominant.
According to this classification, all Belgian regions correspond to the Type 1 Western model with clinical medicine and biomedical research as dominating fields.

**Table II-13. Relative specialisation index (RSI) among Belgian regions**



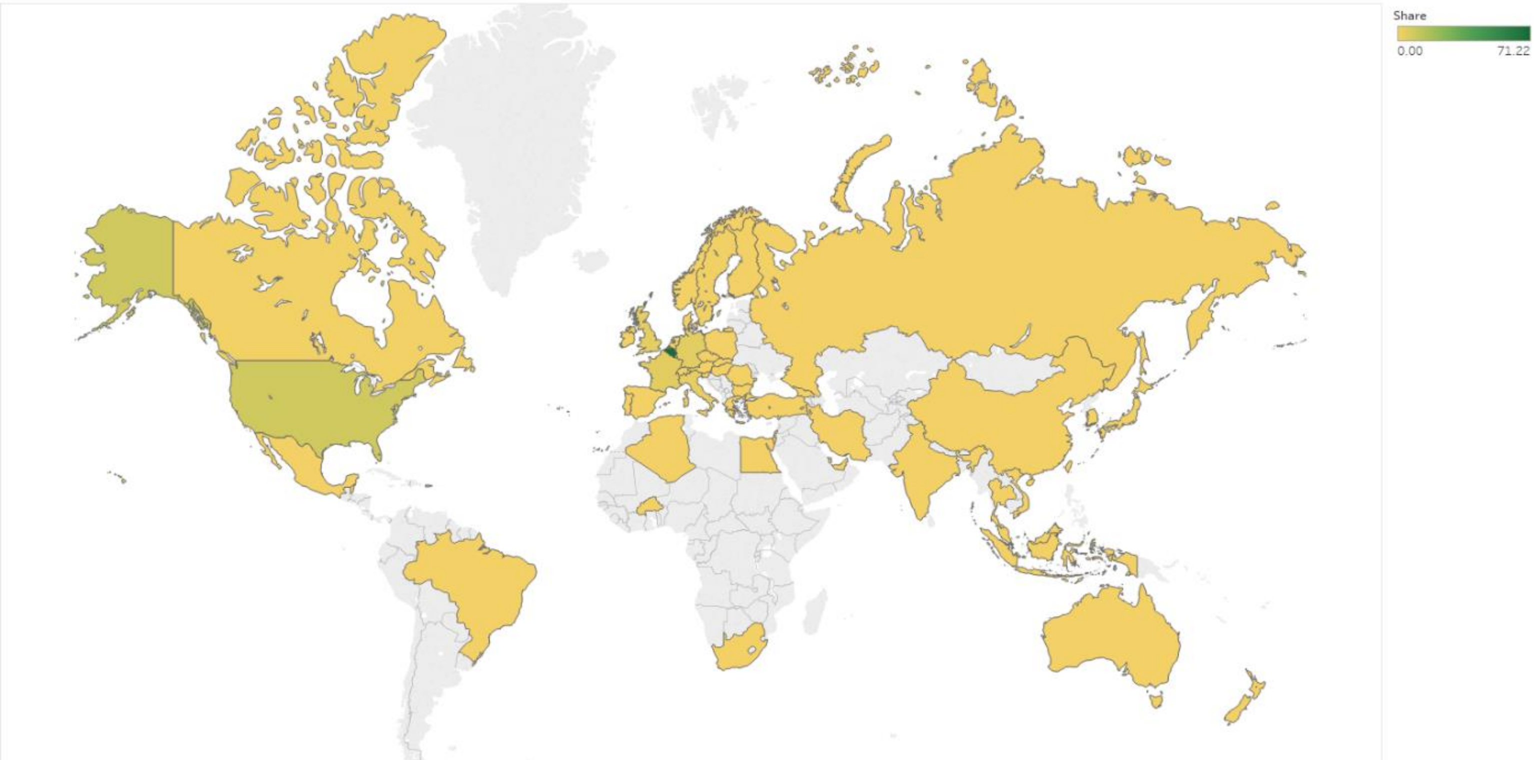

Source: own calculations, Scopus

## 2.7 Global knowledge pipelines: contribution to patents and scientific publications at country level

Figures II 29-34 present a summary statistic based on complete patent and scientific publication datasets for the period 1990-2013. In order to construct this indicator, we used a patent/ scientific publication count methodology for the entire period, where we expand our research to the level of global knowledge pipelines. Only the top 10 countries contributing in patenting/scientific publications with at least one inventor/author located in Brussels are considered. In total, 58 countries are involved in patenting activities and 171 countries in scientific publication performance.

According to the results in Figure II-31, as a non-EU country the United States has the highest share in terms of cooperation in patenting with the Brussels-Capital Region. Rather less cooperation is observed between EU countries, such as France, Germany, United Kingdom, Italy and Netherlands. Switzerland, Japan and Canada represent less than one percent of the total share. The Brussels-Capital Region tends to patent considerably more with the Flemish and Walloon regions (within the country) than with other countries. The Brussels-Capital Region shows stronger collaborative relations with the Flemish region than with the Walloon region. Moreover, a similar number of EU and non-EU countries are involved in patenting performance with the Brussels-Capital Region. The Brussels-Capital Region has the highest share of patent contribution with the Flemish and Walloon regions and the United States.

**Figure II-29. Contribution to patents by country from 1990-2013, all countries**




Source: own calculations, Patstat, Tableau

**Figure II-30. Contribution to patents by country from 1990-2013, the most active countries**

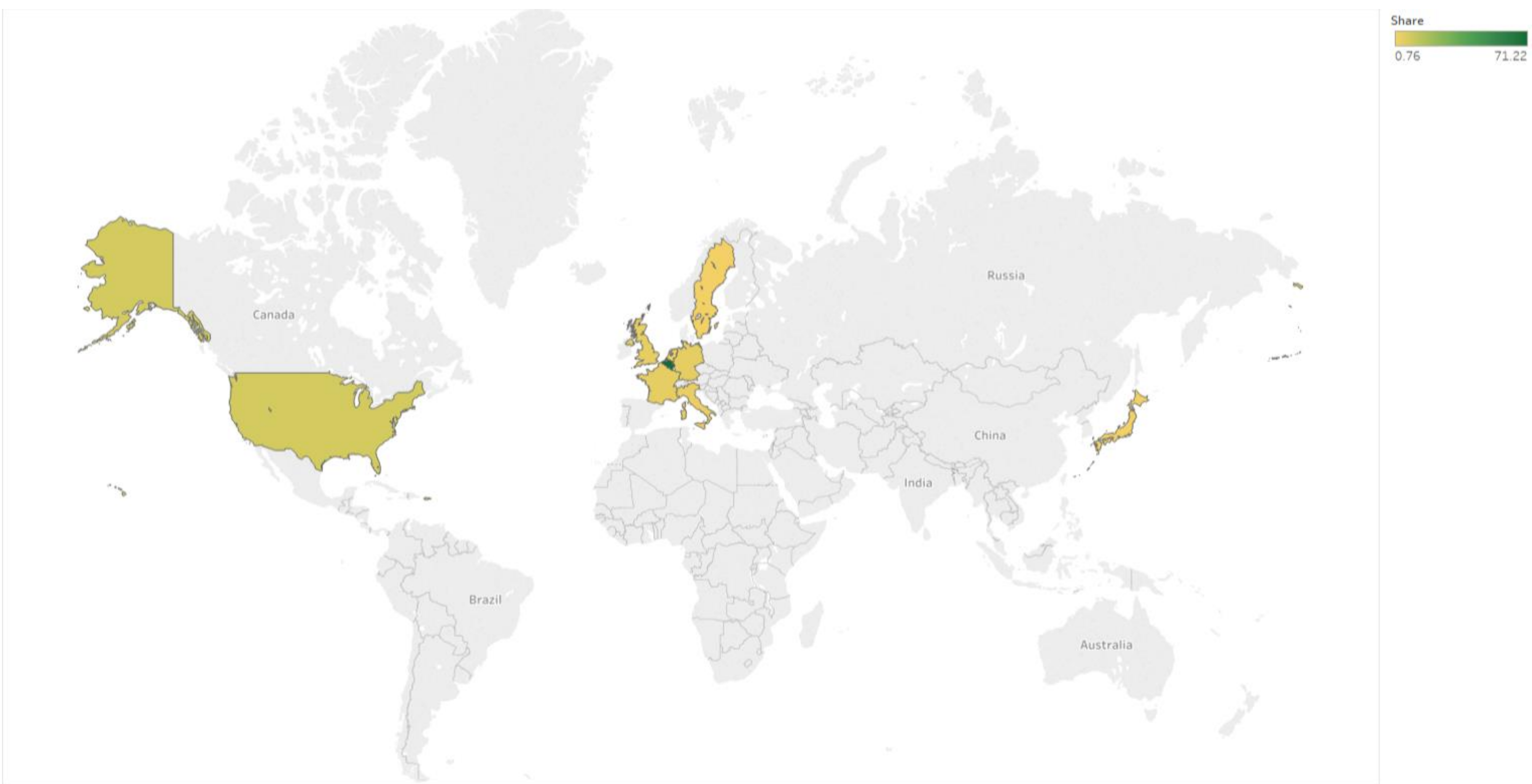
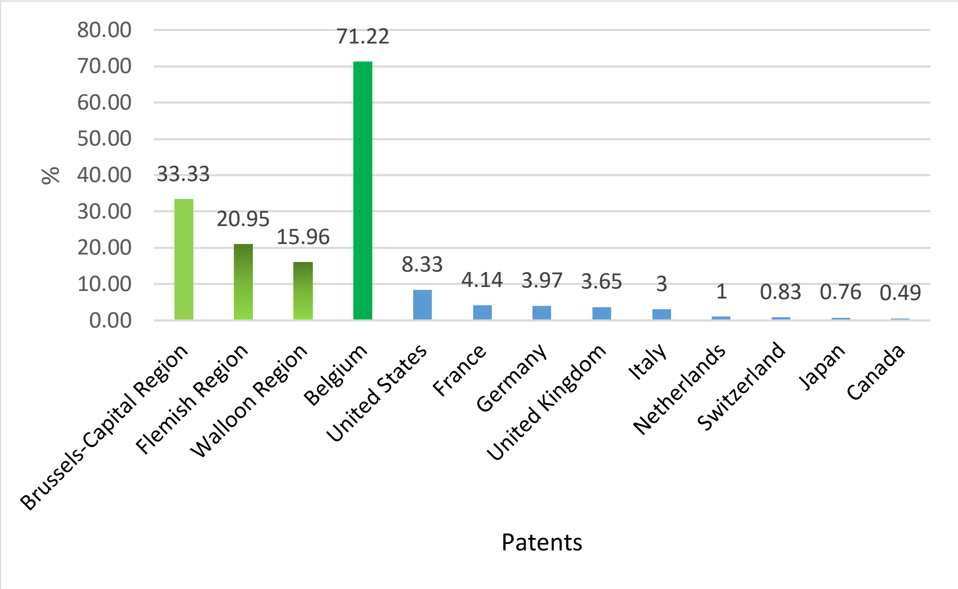


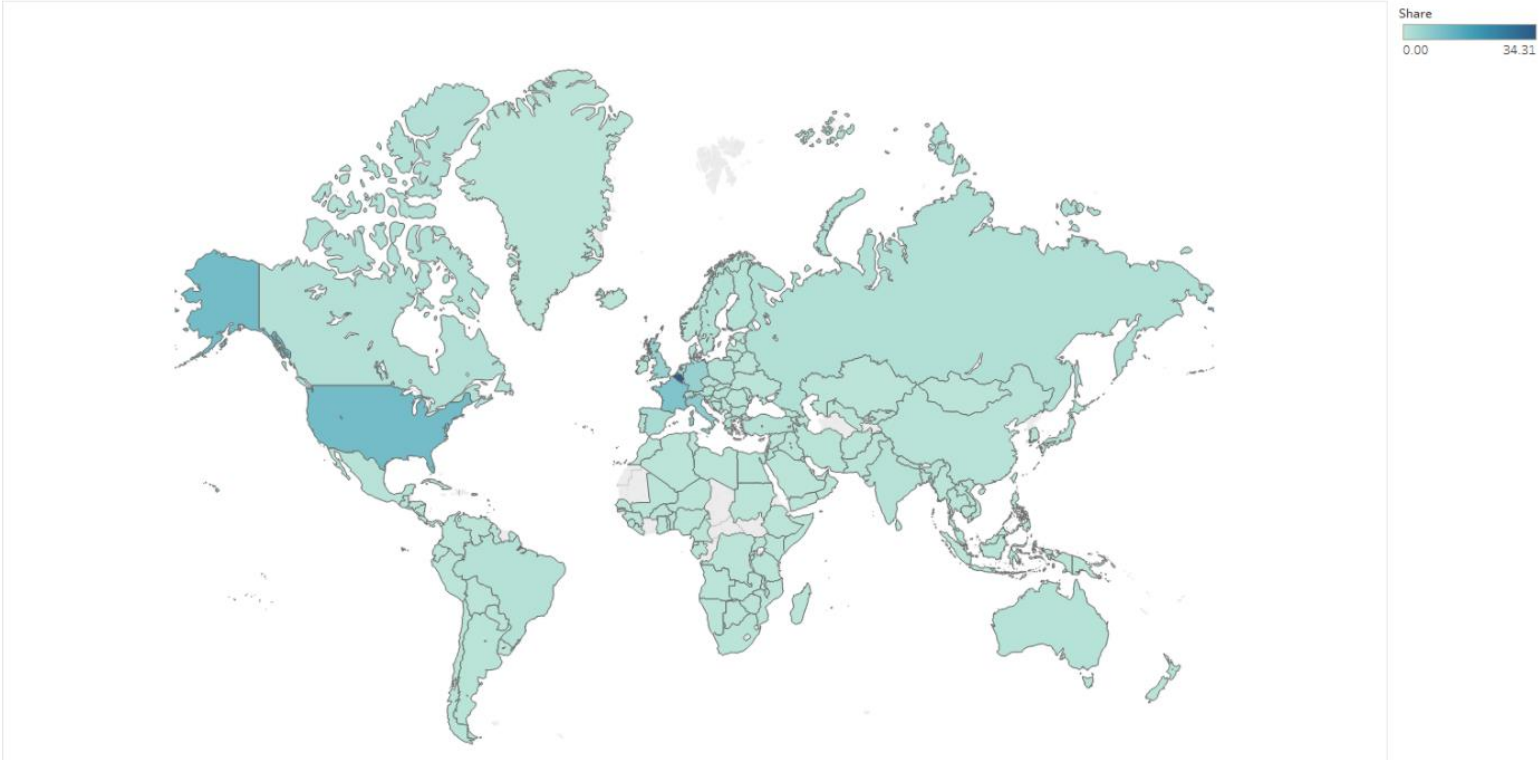
**Figure II-31. Contribution to patents by country from 1990-2013, top 10 countries**




Source: Own calculations, PATSTAT database, Tableau software

The results of the next indicator in Figures II 32-34 show that in general the share of other countries involved in producing scientific publications with the Brussels-Capital Region is significantly higher than the patent statistic. For example, the United States is two percent more engaged in publication than in patenting activities. In fact, three times more countries participate in scientific publication collaboration than in patenting. Moreover, a greater number of EU countries than non-EU ones with a higher share are involved in scientific publication performance. Within Belgium, the Brussels-Capital Region has stronger collaborative relations with the Flemish region than with the Walloon region. Wallonia has a rather low share of participation in terms of scientific publication cooperation with other EU countries. The Brussels-Capital Region has the highest share of contribution to scientific publications with the United States, France, Italy, the Flemish region, United Kingdom and Germany.

**Figure II-32. Contribution to scientific publications by country from 1990-2013, all countries**




Source: own calculations, Scopus, Tableau

**Figure II-33. Contribution to scientific publications by country from 1990-2013, the most active countries**

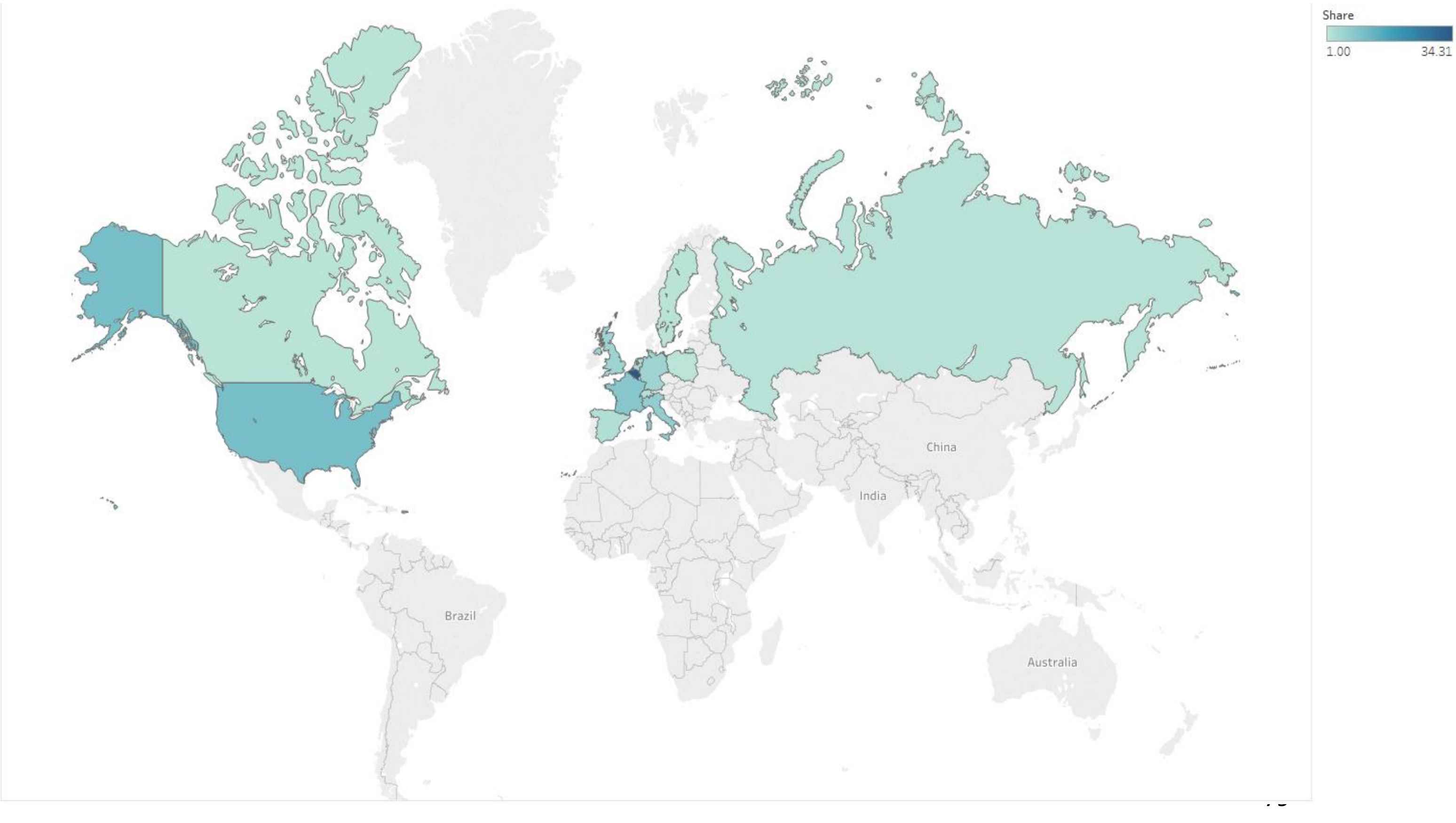
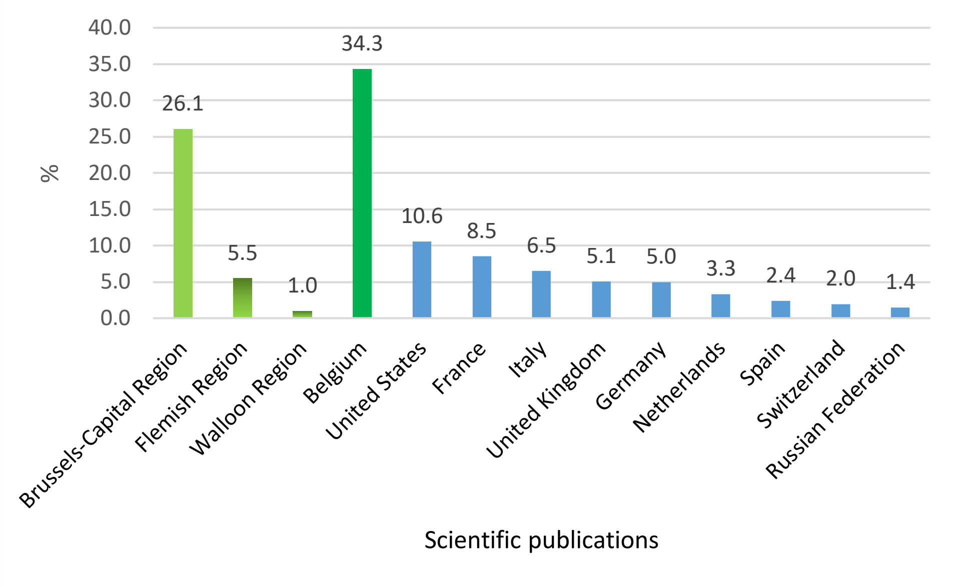


**Figure II-34. Contribution to scientific publications by country from 1990-2013, top 10 countries**




Source: Own calculations, SCOPUS database, Tableau software

## 2.8 SWOT analysis

A SWOT analysis of the Brussels (and its hinterland) innovation system (based on the results for the period 1993-2013) and critical analysis of the adequacy of the current Brussels innovation regional plan to address threats and weaknesses and maximize opportunities and strengths is presented in Figure II-35.

**Figure II-35. SWOT analysis**

| INTERNAL FACTORS | |
|---|---|
| **STRENGTHS (+)** | **WEAKNESSES (-)** |
| 1. Patent performance in the Brussels-Capital Region is higher than in the other metropolitan regions.<br>2. “Medical and veterinary science; life-saving” and “health” technological fields are the most predominant areas.<br>3. Brussels reveals a high technological proximity to more than half the Belgian districts, which is a condition to benefit from technological spillovers.<br>4. More product-oriented patents which are more favourable to job creation.<br>5. The Brussels-Capital and Walloon regions apply relatively more patents in the field of chemistry and pharmaceuticals while the Flemish region seems to be more specialised in the field of instruments.<br>6. The growth in the number of scientific publications over time.<br>7. Brussels generates quality publications slightly more than Vienna.<br>8. Brussels reveals scientific proximity to more than half the Belgian districts. | 1. “University” and “Government non-profit” organisations have a lower number of patent applications in Brussels and its hinterland.<br>2. High dependency of the Belgian innovation system on foreign multinationals lowers the propensity to patent.<br>3. “Companies” have the lowest performance in terms of scientific publications in the whole hinterland.<br>4. More countries participate in scientific publication collaboration than in patenting |

| EXTERNAL FACTORS | |
|---|---|
| **OPPORTUNITIES (+)** | **THREATS (-)** |
| 1. To increase the number of patent applications from “University” and “Government non-profit” organisations through policy implications and stimulations.<br>2. To enhance the private rates of return through process-oriented patents.<br>3. To strengthen scientific collaboration between Companies and Universities, which will increase the scientific publication input.<br>4. To expand patent collaborations with EU-countries.<br>5. To involve more non-EU countries in scientific publication collaborations. | 1. In terms of patenting, Brussels has the lowest relative share in three main strategic domains in comparison with the other metropolitan regions.<br>2. The distribution of scientific publications among strategic action domains shows rather small shares. |

## 2.9 Conclusion and policy implications

The research on patent and bibliometric indicators brings together a new collection of statistics depicting recent trends and the structure of patent and scientific production in Belgium and comparable European cities.

The analysis presented in this report suggests a series of issues and possible policy implications. Our awareness in terms of knowledge flows remains insufficient, and future studies should be devoted to improving this. Many questions in this sphere have not yet been fully investigated: How does information circulate between the various actors? How are agreements settled? What is the role of intermediaries?

The indicator-based analysis is useful to determine progress over time against various objectives providing information relevant to policy, measure performance against a target to evaluate the effect of policy actions and plans, as well as, to present information to the public or stakeholders in a simplified way. Indicators are used in establishing baselines, monitoring, and evaluation. Innovation and Technological change are two main areas of economic analysis in the industrialised countries, as they can determine the factors of the productivity and competitiveness of a nation. Science and technology (S&T) activities are key for fostering technical innovation, and therefore there is an increasing interest in describing the countries', regions' or cities' S&T activities. In most of the cases, S&T activities are measured by using indirect input, output and impact indicators. The patent data is used as an output indicator. Patent-based indicators can be very interesting for assessing the performance of application-oriented types of R&D. Although patents do not cover all kinds of innovation activity, they do cover a considerable part of it. Analysing S&T patterns, it is recommended to systematically and continuously monitoring patenting activity. Meanwhile, patent indicators should be complemented with other S&T indicators, in order to be able to have a complete view of the innovation activities of the countries, regions or cities for example. Researchers and policymakers are committed to using related indicators or ‘proxies’. Patent statistics are an appropriate ‘proxy’ for technological and innovative activity. The analysis of patent information is considered to be one of the best established, readily available and historically reliable methods for quantifying the output of science and technology systems. Patent-related indicators have a number of methodological and technical benefits, but – like any other indicator – they have limitations that must be taken into account. Bibliometrics is the quantitative analysis of publications. It essentially extracts data from publications and analyses that data in various ways to answer questions about the research that those publications represent. Bibliometric indicators complement and contribute the efforts to standardise, collect, report and analyse a wide range of science, technology and innovation activities by providing evidence on a selected set of S&T outcomes.

Patent statistics provide elements to measure the results of resources invested in research and development activities, and trends in technical change over time. Patent analysis is also a valuable approach that uses patent data to obtain information about a given industry or technology. Today patents can be used to understand the past and even potentially to forecast the future. Patenting helps to explore, organise and analyse large amounts of data, helping researchers to identify “hidden patterns” that may assist in the decision-making process. Patents are of interest to economists, industrialists and policy makers for three main reasons: they help stimulate investment in innovation, they contribute to monopoly power, and they are a rich source of qualitative and quantitative information on technological change (Kürtössy, 2004).

The differences in patenting behaviour across industries and countries over time are the most studied phenomenon (Khan and Dernis, 2006.) In fact, not all inventions are patented and there are many reasons for that. For example, companies can prefer secrecy, or rely on other mechanisms to gain market dominance. Different standards across patent offices over time affect patent numbers although R&D activities may remain unaffected.

Patent data highlight the position and specialisation of regions, districts and countries across areas and different fields in our study. Overall, the Brussels-Capital Region tends to patent relatively more than other Belgian regions, city agglomerations or districts since the analysis is based on patents with inventors located in Brussels. With regard to the analysis made between comparable capital cities of metropolitan regions, in terms of patent applications Brussels performs more efficiently than Berlin and Vienna.

There is also evidence that Companies and Individuals tend to patent more than Universities and Government non-profit organisations at all spatial levels. One potential explanation is that the high cost of the patent application procedure might cause Universities and Government non-profit organisations to choose not to patent or patent less. The other issue is that due to the delay in patent filing and academic publications, there is reduced diffusion, etc. Based on these facts, the government might consider a series of policy measures aimed at fostering the diffusion of university research. In addition, changes in patent regimes might contribute to an increase by making patents more valuable and easier or less costly to obtain. Stimulating Universities will increase the number of patent applications.

Another important segment of our research indicates that the ICT and Environment sectors are less present than other sectors (for example, Health and Medicine) in regions and city agglomerations. The comparison between metropolitan regions showed significant growth in the ICT sector, but this sector shows the lowest performance. Most patent offices have seen a surge in patent applications in the past two decades, with the largest contribution to growth being made by ICT. The expansion of ICT, which is reducing communication costs, may increase the number of forms of collaboration, from sponsored and collaborative research to strategic alliances, mergers and acquisitions, and technology licensing.

As patents play an essential role in market-centred systems of innovation, economic criteria should be used more systematically to evaluate patent systems’ ability to foster innovation and to encourage technology diffusion and knowledge flows. In future research it would be interesting to analyse in depth the collaborative relations between different organisations for a district-level aggregation.

Today, bibliometrics is one of the rare truly interdisciplinary research fields to extend to almost all scientific fields. Scopus indicators reflect scientific output, as measured by journal count. The basic indicators of scientific publications still have a long way to go, providing an essentially objective quantitative measure of scientific output. Researchers are pursuing their efforts to apply and improve existing indicators. Each indicator has its advantages and limitations. The various procedures and methods need to be used in combination for scientific publication indicators, despite the contradictory results, as long as they offer useful information and comply with scientific and professional standards.

Belgium in general has strong research universities as reflected in the number and quality of scientific publications. Publication growth has been mainly concentrated in higher education institutions, reflecting the increasing share of higher education R&D expenditure at all spatial levels. Policy implications should continue to nurture high quality research performed in the public sector. This involves maintaining healthy funding streams for research. Additionally, better exploitation of the results of this research in commercial terms could be achieved by fostering S&T collaboration between public research institutes and private companies. Further stimulation of funds from industries will promote more collaboration with Universities and Government-non-profit organisations. Concerning the coherence between the scientific and technological fields of specialisation in the Brussels-Capital Region, another recommendation may be to develop clusters and smart specialisations.

To better understand the topic, a more refined evidence base is necessary for policy making. We recommend refining data collection in PATSTAT and Scopus allowing a geographical link to be formed between private innovation actors in Brussels and collaboration or sources provided by public research actors within (local buzz) and beyond (knowledge pipelines) the borders of the region or city agglomeration. In addition, attention should not only be paid to the existence of these knowledge interactions, but also to their relevance and content.

This Chapter on the science and technology knowledge stock and flows in the Brussels-Capital region and its hinterland provides important learnings and highlights improvement suggestions geared towards policy makers and other decision-makers concerned with the local buzz and global pipelines activities on how knowledge exchange takes place when Brussels actors are involved and which partners, locations, scientific fields and technological sectors are preferred.

## CHAPTER III

# R&D AND PRODUCTIVITY PERFORMANCE OF FIRMS IN BELGIUM: A SPATIAL ANALYSIS

This chapter is based on the INNOVIRIS project "Prospective research for Brussels 2014", "Brussels knowledge flows: localised learning and regional knowledge pipelines (BLOCPIPE)", ULB, Belgium.

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## SUMMARY

*The topic of the spatial pattern in R&D activities was investigated by several scholars. It is worthwhile to explore the dynamism and change of R&D activities' spatial spread as R&D activities are very much a dynamic phenomenon and the consequences in terms of past growth of these activities have painted the current relative position of the regions. Analysing the determinants of the efficiency levels across Belgian regions at different spatial levels (3 regions, 10 provinces, 43 districts, and city agglomerations), we derive a regression based on the measurement of regional output growth by estimating an extended Cobb-Douglas production function based on a representative sample of Belgian R&D active firms over the period 2000-2013. We investigate the role played by knowledge (private and public R&D stocks) on the output growth by applying spatial econometric methods that account for both heteroscedasticity and spatial autocorrelation. The chapter focuses on the comparison of obtained results with previous studies based on Belgium. It turns out that a large part of output growth differences across the Belgian regions are explained by disparities in the endowments of these determinants.*



***Keywords:*** *R&D productivity, R&D intensity, Economic growth, spatial levels*
***JEL codes:*** *O12, O40, R11, R12*

## 3.1 Introduction

It is widely acknowledged that all economies are characterised by strong territorial disparities. These disparities not only exist between countries, but also within countries (Capron, 2000). Nowadays the territorial dimension of regional disparities as an aspect of EU policy has gained importance. (Niebuhr & Stiller, 2003). Several scholars have examined the reasons of territorial disparities among European countries.

Several scientific studies have indicated that regions have become more important than countries in the creation of economic growth in the period of globalization (Castells & Hall, 1994; Storper, 1997; Porter, 2000; Camagni, 2002). Innovation capability and competitiveness of firms and regions are stimulated by the importance of the regional scale and the importance of specific regional resources (Asheim et al., 2003; Cooke, 2003; Wolfe, 2003; Isaksen, 2006). Regional disparities are larger and more persistent when compared to cross-country differences (Magrini, 2004). Baumont & Huriot (1999) integrated new spatial economic theories and growth theories for better explanations in regional growth studies. They, first, emphasize the role played by geographic spillovers in growth mechanisms. Second, they emphasize that most of the analysis points out the dominating growth - geographical patterns of Core- Periphery equilibrium and uneven development. The development of new growth theories attracted most of the attention and at present time integrated different aspects of technological progress and innovation.

The topic of the spatial pattern in R&D activities was investigated by several scholars (Kleinknecht & Poot, 1992; Fritsch, 2000; Bode, 2004; Verspagen & Schoenmakers, 2004; Teirlinck & Spithoven, 2005; Fritsch& Slavtchev, 2011). It is worthwhile to explore the dynamism and change of R&D activities' spatial spread as R&D activities are very much a dynamic phenomenon. The consequences in terms of past growth have painted the current relative position of the regions. In the economic domain, various studies stress the importance of the location of enterprises that decide to invest in R&D. The spatial dimension plays a very important role in establishing the effects of interaction among the agents of the same group, pole or agglomeration and can influence the R&D activity of the firms within the selected area. Spithoven & Teirlinck (2001) state that the lower spatial level such as district has some useful social (e.g. universities, incubation centers, highly skilled labor market, etc.) and physical (e.g. airport, good accessibility, adequately equipped sites, etc.) infrastructures that exert positive effects on R&D activities. In line with the bottom-up ideas embodied in the endogenous growth theory and the upsurge of cluster policies and the networked economy, there is a growing interest in the provinces (i.e. NUTS 2 level) studying innovation and R&D activities (see e.g. OST, 2002; European Commission, 2003).

This chapter proposes to discuss the following research question: whether the different spatial levels can be accounted as a factor influencing productivity growth of R&D active firms and whether spatial disparities are shrinking. Besides, this chapter extends the existing literature in several ways. First, we analyse lower spatial levels such as provinces, districts and city agglomerations which provide a clearer view on a more detailed country profile of Belgium and its spatial disparities. Second, we focus on a comparison of obtained results with previous investigations about Belgium and its spatial differences. Finally, this work aims to also assess the output growth by using the Cobb-Douglas production function model (Hall et al., 2010), with regard to the different spatial dimensions.

The chapter is structured as follows. Section 3.2 presents some stylised facts about Belgium. We discuss the theoretical background and related empirical literature in the Section 3.3. Section 3.4 deals with the data sets used in the empirical analysis, descriptive statistics as well as the econometric framework. Section 3.5-3.6 presents the specification of the empirical framework and the analytical results with robustness checks. Final remarks and avenues for further research are discussed in Section 3.7.

## 3.2 Stylised facts: Belgium

Belgium is appearing as one of the most interesting example of spatial inequalities. This country comprises the federal state, three regions (Flemish Region, Walloon Region, and Brussels-Capital Region), and three communities (Flemish Community, French speaking Community, and German-speaking Community). There is a further subdivision into 10 provinces (five Flemish, and five Walloon provinces), and 43 districts. To illustrate different profiles of Belgian regions and provinces we present Gross domestic product (GDP) at current market prices by NUTS 2 regions in 2016 in Map 1.

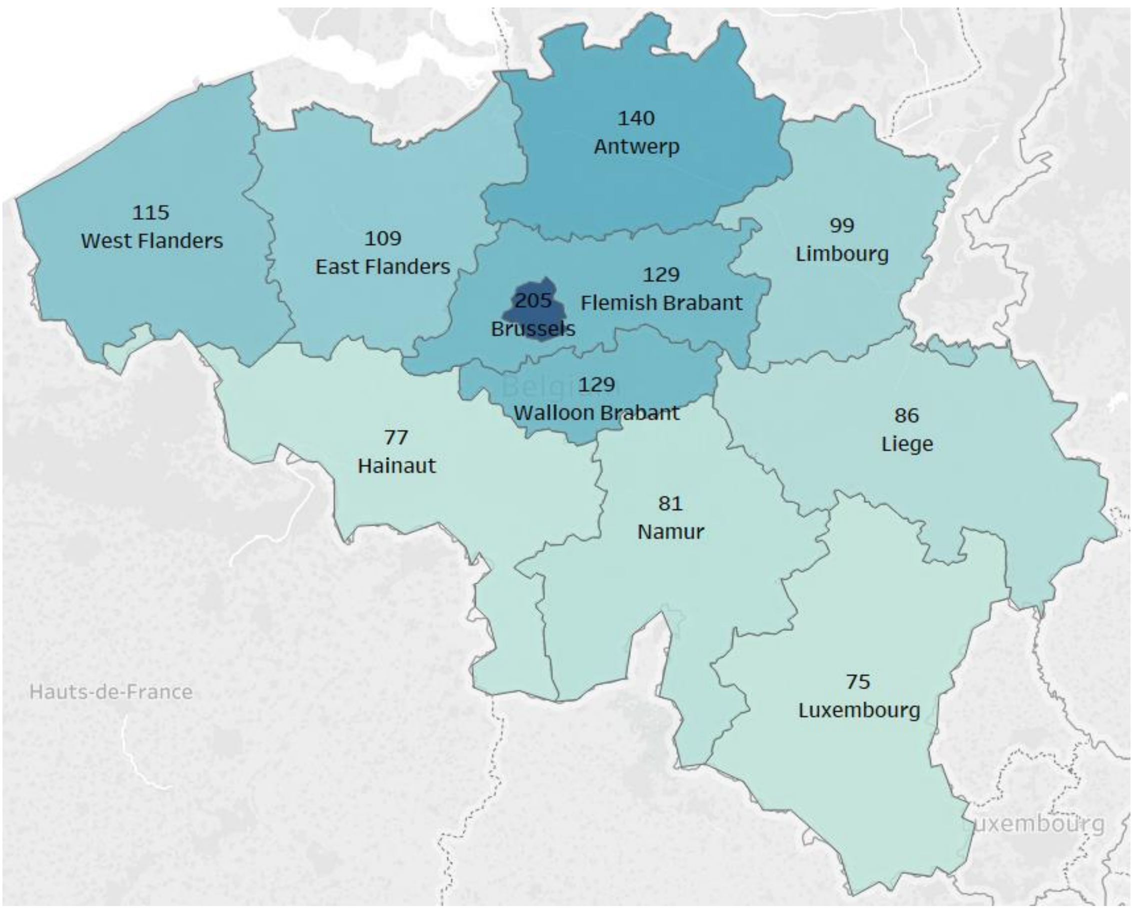
Historically, the Walloon Region was considered as a first comer of the industrial revolution, and the Flemish Region was as latecomer. After the Second World War the situation had been changing and the leading position was taken by Flemish Region (Capron & Meeusen, 2000). Such transformation was caused by several factors such as the diminution of the mining activities in the Walloon Region and, in addition, combined with a concentration of direct foreign investments in the Flemish Region which accelerated the evolution of regional disparities (Capron & Meeusen, 2000).

The Brussels-Capital region is rather international and characterized by a high presence of services and administrations, it attracts high potential labor force as well as large companies (EU authorities, NATO) (Teirlinck et al., 2015*)*. The bilingual Brussels-Capital Region is not subdivided into provinces or districts. This region contains 19 autonomous municipalities, which are referred to as the city of Brussels. In the region, there are many high education and research institutions as well as firms which perform innovative activities. Brussels is the most important Belgian region in terms of economic activities and investment incentives. The R&D system is to a large extent oriented towards product innovation. The Brussels-Capital Region indicates quite high R&D indicators, while industrial R&D expenses have been decreasing over time. The R&D intensity of the Brussels-Capital Region lies below the European and Belgian average. This can be explained by the relative weaknesses of the industrial fabric of high and medium-high technological sectors where usually the level of R&D intensity is high, such as pharmaceutical or electronic industry. Thus, this deficit is understandable as the Brussels-Capital territory is an international city and strongly related to administrative functions (Vaesen, Wayens et al., 2014).

The Brussels regions provides different financial support programmes with each different eligibility requirements in order to improve the innovative performance of the region.

The Walloon Region is a relatively small region which situates in the South of Belgium, 3.37 million inhabitants, 65440 businesses, and French is the main language of this region. The Walloon Region is opposite to the Brussels-Capital Region, it indicates weak R&D expenditure intensity. This region has insufficient development of research but shows rather promising potential. The Walloon Region's research policy places an emphasis on the exploitation of public research output in the economic sector and the enhancement of technology diffusion in companies. The economic performance of the Walloon Region has a gradual tendency to catch up with other very dynamic European regions such as Flanders.

**Map 1. Gross domestic product (GDP) at current market prices per inhabitant in percentage of the EU-28 average=100 by NUTS 2 regions**




Source: Gross domestic product (GDP) at current market prices by NUTS 2 regions for 2016, Purchasing power standard (PPS) per inhabitant in percentage of the EU-28 average=100, OECD.

The Flemish Region comprises the Northern part of Belgium. The region consists of the five Flemish provinces (West Flanders, East Flanders, Antwerp, Limburg and Flemish Brabant). It is a small region with the presence of external competition and tendency to innovate on a permanent basis in order to compete in the global economy (Aerts & Czarnitzki, 2004). Aerts and Czarnitzki also indicate, that after the industrial revolution, the Flemish Region has been developing faster than the other Belgian regions. The Flemish Region specialises more in the manufacture of instruments while the Walloon and Brussels-Capital Regions are mainly concerned with the chemical and pharmaceutical industries. This region shows the highest R&D productivity and number of patent applications. The major actors in the Flemish scientific research system are Five Flemish universities (K.U. Leuven, University of Hasselt, University of Antwerp, University of Gent and VUB). In the French scientific research system there are ten universities (UCL, ULB, ULG, UMH, FUNDP, FUCaM, FUSL, GEMBLOUX, FPMs and FUL).

## 3.3 Literature Review

### 3.3.1 The role of regional development

Regional innovation systems are often analysed as administrative regions, presented as independent ecosystems based on interactive linkages between various types of regional actors (Cooke et al., 1997; Iammarino, 2005). In order to knowledge exchange (Grillitsch and Trippl, 2014); R&D spillovers (Paci and Usai, 2009; Marrocu et al., 2013) or networking effects (Varga et al., 2014) administrative regions are used. Many scholars confirm the use of administrative regions, indicating that regional innovation systems underline the importance of interactions between various actors in the system and as well offer a favourable environment for collective learning, innovation and entrepreneurship (Cooke et al., 1997; Trippl et al., 2017). According to the literature, regional innovation systems (RIS) are characterized by many interacting actors pursuing each their interests, accepting formal organisations and reacting in accordance with institutional arrangements and help to expand the opportunities for localised learning and facilitate the exchange of tacit knowledge flows (Asheim and Isaksen, 2002; Caniëls and van den Bosch, 2011).

With regard to regions, they are presented as politically structured systems focusing on economic development growth and implementation of science and innovation policy. Sanz-Menéndez and Cruz-Castro (2005) state that this is very important for ‘federal’ states such as Germany, Switzerland, Spain and Belgium but is also can be found in ‘unitary states such as France, Sweden and the Netherlands.

The policy of decentralization and regionalization is a growing trend in Europe (Sanz-Menéndez and Cruz-Castro, 2005). However, it is rather difficult to replicate region-specific developed knowledge in other regions (Balland and Rigby, 2017). The emphasis on regional differences is fully consistent with the scholars who observe the growing role of regions and also relate this to science and innovation policy which can be explained in a few ways (Storper, 1995; Fritsch and Stephan, 2005). First, R&D activities are unequally distributed over space (Teirlinck and Spithoven, 2005). Second, regional innovation systems function differently in different regions (Tödtling and Trippl, 2005). Third, regional science and innovation policy are aimed at regional development and can be counterproductive for national (and European) goals that require coordination (OECD, 2013). Fourth, the study of regional policy can contribute into benchmarking and comparison for policy makers to learn from each other (Fritsch and Stephan, 2005).

Regional innovation systems also belong to spatial entities with at least some degree of autonomous political power (Cooke et al., 1997; Uyarra, 2010), which is explains that the regional (NUTS 1) level in Belgium is instructive. Moreover, science policy is largely regionalized according to the NUTS 1 classification. The main regions are the Brussels-Capital Region, the Flemish Region and the Walloon Region (Belgian Science Policy Office, 2010). There are different systems across Belgian regions to allocate regional resources to stimulate R&D activities, although the common goals are similar for most European regions.

The consideration of administrative regions also reflects the idea of the regional embeddedness. According to Sternberg and Litzenberger (2004), regional embeddedness indicates a vague idea of mutual understanding, trust and closeness at the regional level. Other scholars associate this with the actions of people who have unique historical, cultural and other knowledge about the region (Dahl and Sorenson, 2012). This regional embeddedness leads to greater opportunities for identifying and mobilizing resources. Hence, organisations of the region have a common local culture that promotes knowledge spillovers through social and cultural norms, and its functioning is due to the interaction between different types of subjects localised in one region. Miguélez and Moreno (2015) reveal that the existence of regional absorptive capacity can also contribute to the effectiveness of knowledge exchange mechanisms. In the work of Kramer and Revilla-Diez (2012), the authors indicate that regional embeddedness points to the existence of 'sticky' knowledge and intangible assets which are rather difficult for firms to capture and absorb if the firm’s location is outside the region. However, Malecki (2010) and Bathelt et al. (2004) characterize the embeddedness of relationships as positive externalities from regional and local integration which is connected to the knowledge repositories, expertise and skills and which is hardly reproduced in other regions (Asheim and Isaksen, 2002).

### 3.3.2 Territorial disparities

In geographic acceptation, territorial disparity refers to an inequality that is "felt, perceived and lived as an injustice" (Brunet et al., 1992). This inequality can correspond to a difference in economic, social, cultural etc. dimensions. Disparities attracting attention if they have an impact on the functioning of territory and economic development (Aydalot, 1985).

The uneven development of regions is a barrier for realising the cohesion objective of the EU. Primarily, the focus of regional disparities policies was on unemployment, industrial reconversion and agricultural modernisation but has broadened to include disparities in innovation, education levels, environmental quality, and poverty and social exclusion. The cohesion objective had been extended by a territorial dimension of cohesion. Therefore, the spatial planning in the member states of the EU aims at a spatial balance which in turn will support an even growth across the territory of the EU. This concept led to the adoption of the European Spatial Development Perspective (ESDP) (Niebuhr and Stiller, 2003). The aim of the ESDP is to create an agreement between the member states and the European Commission in terms of common spatial objectives concerning the future growth and development of the EU territory. The study of territorial disparities provides with new aspects due to various functional linkages between agglomerations and other regions. That way the importance of urban areas as growth centres and sources of beneficial spillover effects progressing economic development in neighbouring regions is emphasised (Funke and Niebuhr, 2005).

The academic interest in regional and spatial disparities occur from the ongoing debate on the growth of an economy. Petrakos et al, (2016) in their work indicate that spatial disparities tend to decrease due to catch-up growth of less advantageous economies arising from a higher marginal rate of return on invested capital in faster-growing economies. The growth is considered as a cumulative process that might depend on different conditions and demands a minimum of resources and activities in order to be succeeded (Petrakos et al 2015). Lundvall (1998) assumes that disparities can be explained by differences in the knowledge bases and not by differences in factor proportions, as assumed in the standard neoclassical theory. In order to achieve long-run economic success (Romer, 1990), broader economic aspects should be considered including institutional arrangements, levels of education, investment in R&D. Romer (1990) in his work emphasises that regional disparities cannot be diminished by a mere compensation of capital-output ratios but also market incentives and government policies should be actively enrolled in reducing inequalities.

Much of the academic literature on spatial disparities has rather narrow focus (Banerjee and Jesenko 2015; Istrate and Horea-Serban 2016). However, spatial inequality has to be determined more broadly as it might exist in different places in order to be able to support the possibility of growth. It also facilitates the change in EU thinking from seeing the differences as ‘deficits’ in weaker countries/regions/districts to 'conceptualising them as potentials’.

### 3.3.3 Importance of city-agglomerations as innovation systems

The relation between cities and innovation is the central topic in the literature (Shearmur, 2012). In this chapter we also consider the functional territory of the city-agglomeration. A number of scientific studies state that the city surrounding is closely linked with the core city in terms of labor mobility, which is an important component for knowledge exchange (Luyten and Van Hecke 2007). The location can play an important role in terms of generation of new innovations which in turn can enhance the technological advance and economic growth (Krugman I991a, b; David and Rosenbloom 1990). In addition, Healey (2004) states that functional relationships influence the interaction between cities and their regions.

City-agglomeration is characterized as growth centres with a concentration of human capital, the primary source for knowledge and the primary vehicle for its flows and transfer, and knowledge which can spill over between actors (Spithoven, 2018). Jonas and Ward (2007) states that functional city-agglomerations are more useful for studying innovation in a global economy. Trippl et al. (2017) emphasize that the city agglomeration of R&D knowledge base covers an environment in which innovative firms create and expand their potential in engaging and absorbing external knowledge from various sources. Simmie (2002) introduce city-agglomerations as hotspots for innovative companies because of their concentration of local capacities and international relations.

### 3.3.4 Empirical insights

Analysing spatial disparities in our work through productivity growth, we would like to make a short literature review on the topic of productivity growth and R&D returns. This chapter builds on already large body of literature examining the relationship between productivity growth and R&D returns. For a long time, economists have been developing various methods to estimate the rate of returns to R&D. The main approach to do this mostly relates the growth of total factor productivity (TFP) to R&D. The purpose of this section is to review main theoretical arguments as well as empirical findings on R&D and productivity performance.

Most of the research that measure the returns to R&D (at micro or macro levels) relies on a production function framework, where the output is related to the stock of R&D (or knowledge capital). In the work of Hall et al. (2010) the authors conclude that R&D rates of return in developed economies have been strongly positive during the past half century, as well as the estimates based on industry-levels or company-level data. The differences in changes in R&D elasticities can be divided into two streams of literature. The first belongs to the scholars who`s research is based on US company or industry data, and the second part represent the scholars who produced their research based on European company or industry data. This distinction is important in terms of visual comparison of different outcomes.

US scholars draw on the work of Griliches (1980), who estimated an R&D elasticity of 0.07 based on a production function which includes sectoral dummies. Schankerman (1981) considered the same period as in Grilliches's study, using less observed companies (110 US firms), and calculated an R&D elasticity of 0.16. Griliches and Mairesse (1984) estimated the coefficient of 0.05 for R&D elasticity in the case of 113 US firms. In the research of Griliches (1986) and Hall et al., (1993) for US firms the R&D elasticities vary between 0.09 to 0.17 and 0.024 to 0.040 respectively. Bartelsman (1990) used TFP and R&D stock and the R&D elasticities ranged from 0.11 to 0.15 for 450 industries. In addition, Los and Verspagen (2000) found R&D elasticities for 485 firms ranging between 0.04 to 0.10. Hall et al., (2009) established an R&D elasticity equal 0.096 in the case of 1,513 firms from US.

Scholars looking at the European evidence also researched the topic. Cuneo and Mairesse (1985) estimated an R&D elasticity of 0.22 using a double counting method for 390 French firms. Considering French companies Hall and Mairesse (1994-1995) showed that, using industry dummies, diminishes the R&D elasticity from 0.25 to 0.176. Some of the effect from industry dummies is due to permanent differences across industries both in the propensity to do basic research and in their productivity growth. Bartelsman et al. (1996) found that R&D elasticities in Netherlands ranged between 0.006 to 0.014. The same framework is used by Harhoff (1998) for Germany and resulted in an R&D elasticity of 0.14 and 0.11. Griffith et al. (2006) reported an R&D elasticity of 0.03 in a panel of 188 manufacturing firms listed on the London Stock Exchange in 1985. Verspagen (1995) used country data and industry dummies for 9 OECD countries and calculated R&D elasticities ranging between 0.05 to 0.17.

Based on the Belgian experience, Everaert and Heylen (2001) analysed the impact of public capital on private sector productivity in Belgium applying a Cobb-Douglas model for the period 1953-1996. The results showed a significant positive relationship between public capital and private sector productivity, where the estimated output elasticity of capital is nearly 0.29.

Cincera et al. (2003) provide further evidence for Belgium on the important role of knowledge in explaining performance at the company level, by augmenting the classical productivity growth approach not only with own R&D expenditures, but also with R&D cooperation, where they use company level data on R&D and productivity. The results exhibit that R&D intensity exerts a positive and significant influence on productivity growth, with a rate of return to R&D investment of 13%. Additionally, the international R&D cooperation has a strong and significant effect on productivity growth. Using industry level data, Biatour et al. (2011) estimated the impact of the determinants of total factor productivity (TFP) for Belgium for the period 1988-2007. Econometric results inferred that R&D is an important determinant, either R&D accumulated inside the industry (intra-industry) or R&D accumulated by other domestic or foreign industries (inter-industry) (Biatour et al., 2011). Dynamic OLS estimation of the determinants of TFP for a panel of manufacturing industries in Belgium showed that domestic R&D (patent-weighted) is 0.3, for services, construction and utilities is 0.03 and for manufacturing industries grouped by R&D intensity is 0.01.

Belderbos and Van Roy (2010) investigated at what extent the total factor productivity (TFP) of local companies can be influenced by the presence of affiliates of foreign multinationals. Significantly positive effects of horizontal (domestic companies) and backward spillovers (foreign multinationals) on the productivity levels of local companies were revealed. The authors further emphasized the importance of internationalization for productivity and welfare growth, both through the internationalization of domestic companies, and through foreign direct investments by multinational companies.

Teirlinck and Spithoven (2005) detected an unequal spatial pattern of R&D activities in private business enterprises at the district (NUTS 3) level in Belgium in 2001. Their main results showed that there is a big difference in R&D performance between 43 districts in Belgium. This inequality being higher than that in terms of gross regional product (Teirlinck & Spithoven, 2005). As can be seen from empirical side that R&D expenditures in a district are positively influenced by R&D specialisation and concentration. Moreover, for the R&D active companies we can observe a significant negative impact of R&D concentration. In small open economies the proximity to the public knowledge infrastructure can help explain business R&D activities. Spithoven and Teirlinck (2002) highlight the spatial dimension of the R&D expenditures in the business sector in Belgium. High R&D intensity is correlated with the physical and social infrastructure of the district. The authors assumed that sector and spatial aggregation in Belgium are playing a crucial role in the dynamics of R&D expenditure. Hence, these differences are more visible at the district level then at regional level. There were important differences between districts belonging to the same region at NUTS 1 level.

In summary, from the above considerations we have learned that the rates of return to R&D are positive in many countries: R&D inputs exert a positive and significant influence on productivity growth. Our contribution to this debate is not merely to replicate measurement of the returns to R&D, but to supplement it by including the spatial differences in Belgium and its impact on output growth.

## 3.4 Data and methodology

### 3.4.1 Data

The primary data source is drawn from the Belgian biannual R&D surveys, jointly organised by the Belgian Federal Science Policy Office (BELSPO). This longitudinal unbalanced dataset consist of a representative sample of R&D performing companies in Belgium over the period 2000–2013 and contains 7,652 companies. The survey provides information on companies' in-house R&D expenditure. An important feature of the R&D surveys is that the questionnaires are sent to firms with at least 10 employees. Due to the fact that this information comes from a survey and that the companies were not compelled to answer, the database is strongly unbalanced. To render the database balanced and applicable for construction other variables such as R&D stock, we consider only companies which have R&D expenditure data for five subsequent years. All companies which do not have R&D data for at least five subsequent years are removed. Further, all extreme values of 1% for the ratio added value to average employment are also removed as these observations might refer to errors. As a result, we have a database of 3,686 companies (see Appendix I-1 on the representativeness of the database). These data are matched with financial data covering net added value, physical capital, employment and sector (NACEBEL codes) from National Belgium Bank (NBB) which gathers detailed information on companies in Belgium and Luxembourg. All monetary variables, expressed in current prices, are transformed in constant prices using the GDP deflator (base=2010). The matching between NBB and biannual R&D survey datasets was performed on the basis of the VAT number and the YEAR variable.

### 3.4.2 Spatial proximity

Both in the resource-based perspective and in the regional innovation system, the aspect of spatial proximity plays a key role. First, spatial proximity is assumed to heighten the potentials for interplay, cooperation, coordination, and contacts between the firms and their R&D or innovation partners (Teirlinck et al., 2010), favouring providers within the region itself. Hence the importance of the concept of localised learning. Localised learning outlines the local/regional conditions and their spatial proximity between actors in the system. It explains the origins of regional specialisation (or diversification) and the reasons why firms tend to co-locate. From a resource-based perspective, it is acknowledged that specialised technological knowledge or reputed R&D providers are vital, but they are not necessarily available within the region - especially a smaller one like the Brussels-Capital Region - making spatial proximity a lesser issue (Jaffe et al., 1993). This is, of course, not to negate the fact that important R&D providers are not located outside the borders. Firms in need of specialised knowledge that is in short supply, will source it regardless of its location (Teirlinck et al., 2010). Spatial proximity is, moreover, only one dimension in the requirements form knowledge and technology transfer. In order to test spatial proximity in Belgium we include the regional dimension, use is made of administrative regions to capture regional innovation systems (Döring and Schnellenbach, 2006; Caniëls and van den Bosch, 2011). The NUTS 1-3 classification of a firm is used as an indicator of the local administrative unit. There are three classes in NUTS1: the Brussels-Capital Region, the Flemish Region and the Walloon Region, as well as, eleven Belgian provinces in NUTS 2 and forty three districts in NUTS 3.

Additionally, in this study we use the operationalisation of city-regions based on a large number of different socio-economic and spatial indicators from the most recent census of 2001 (Luyten and Van Hecke, 2007). In total we consider three categories of city-regions when comparing the Brussels city agglomeration to other agglomeration types. Brussels city agglomeration is a special case as Brussels hosts many international organisations (NATO, EU), headquarters of multinational companies, and many higher education institutions (universities, university colleges and university hospitals). A second category consists of four large city agglomerations (Antwerp, Liege, Gent and Charleroi) and the third category has thirteen regional city agglomerations (Brugge, Genk, Hasselt, Kortrijk, Leuven, Mechelen, Mons, Namur, Oostende, Sint-Niklaas, Tournai, Turnhout and Verviers).

### 3.4.3 Basic regression

Based on previous analyses on R&D productivity (Griliches, 1987; Cincera, 2005; Wieser, 2005; Cincera, et al., 2014), a general extended Cobb-Douglas production function is estimated (Hall et al., 2010).

$$Y_{it}=\lambda_t L_{it}^{\beta 1} C_{it}^{\beta 2} K_{it}^{\beta 3} e^{\varepsilon it} \quad (1)$$

where Y is output in terms of value added; L and C are labor and physical capital; K is the knowledge capital; $\beta_1$, $\beta_2$ and $\beta_3$ represent the elasticities of output with respect to each of the inputs; $\lambda_t$ is a set of time dummies and $e^{\varepsilon it}$ is an error term.

In order to estimate the following linear relationship, Eq. (1) is transformed to natural logarithms to estimate the elasticities $\beta_1$, $\beta_2$ and $\beta_3$:

$$y_{it}=\alpha+\lambda t+\beta_1 l_{it}+\beta_2 c_{it}+\beta_3 k_{it}+\varepsilon_{it} \quad (2)$$

where lower case characters denote natural logarithms of variables. The R&D capital stock contributes to differences in productivity among companies and is measured using the Perpetual Inventory Method (Griliches, 1979). This method assumes that the current stock of knowledge is the result of present and past R&D expenditure. The depreciation rate is assumed to be 15% and the presample growth rate is set at 5% (Hall & Mairesse, 1995). In the basic equation industry dummies are added to control for sector-specific and year dummies.

The R&D stock was constructed by using a perpetual inventory method (PIM) (Griliches, 1979). This method is the most commonly used for constructing the firm's knowledge capital. It is assumed that the current state of knowledge is a result of present and past R&D expenditures:

$$\begin{aligned} K_{it} &= (1-\delta)K_{it-1}+R_{it} \\ &= R_{it}+(1-\delta)R_{it-1}+(1-\delta)^2 R_{it-2}+\ldots) \\ &=\sum_{t=0}^{\infty}(1-\delta)^t R_{it-\tau} \end{aligned} \quad (3)$$

where:

$K_{it}$ = knowledge capital or own R&D stock of firm i at time t;

$R_{it}$ = Research and Development expenditures deflated by the GDP deflator;

$\delta$ = rate of depreciation.

In most studies estimated a depreciation rate of 15%. Moreover, several authors, e.g. Hall & Mairesse (1995), have experimented with different values of δ and report very small changes if not at all in the estimated effects of R&D capital. The initial knowledge capital is constructed as above and by assuming a growth rate of presample R&D equal to g:

$$K_{i0}=R_{i0}\sum_{\tau=0}^{\infty}\frac{(1-\delta)^{\tau}}{(1-g)}=\frac{R_{i0}}{(g+\delta)} \quad (4)$$

Here also, a presample growth rate of 5% is usually assumed. As Hall & Mairesse (1995) point out, the precise choice of growth rate can affect the primary stock which in turn declines in importance as time passes.

Summarising, the dataset consists of an unbalanced panel of 7,652 companies in Belgium over the period 2000-2013. In order to have a balanced data and be able to construct other variables such as R&D stock, we consider only companies which have R&D expenditure data for five subsequent years. All companies with no R&D data for at least five subsequent years are removed. Further, all extreme values of 1% for the ratio added value to average employment are also removed as these observations might refer to errors, the final sample has a more balanced panel of 3,686 R&D active companies. Next, the dataset is merged with financial data from National Belgium Bank and divided by spatial proximity. The descriptive statistics and variables' definitions are provided in Appendix I-2 (Table 2.1- 2.2).

## 3.5 Findings

### 3.5.1 Country level

The dependent variable in the analysis is presented by the output growth, in terms of value added, over the period 2000-2013. Ordinary least square (OLS), fixed and random effect with using stochastic regressors as Hausman test and quantile regressions are used to estimate the importance of various determinants of the company's output growth. Fixed and random effects models allow us to control for possible unobserved firms' fixed effects.

Alternative estimation methods are used to examine the robustness of the results in Table III-1. Heterogeneity is often found across firms. Therefore, quantile regression techniques can significantly help us to obtain a more complete picture of the underlying relationship between innovation and firm growth (Mosteller & Tukey, 1977). While OLS can be inefficient if the errors are highly non-normal, quantile regression is more robust to non-normal errors and outliers. Quantile regression also provides a richer characterization of the data, allowing us to consider the impact of a covariate on the entire distribution of output growth, not merely its conditional mean.

Table III-1 reports the results from the estimation of the baseline equation. The dependent variable is the natural logarithm of value added growth in the period 2000-2013 (y). The variable on R&D stock indicates towards a positive and significant influence on output in terms of value added growth (y), with a rate of return to R&D stock of 4.3 %. This means that one unit of R&D will lead to a growth in output of 0.043, or an R&D elasticity of 4.3 %. Similar results can be found in the work of Griffith et al. (2006) reported an R&D elasticity of 0.03. Verspagen (1995), using country data and industry dummies, estimates R&D elasticities of 0.05 to 0.17 (uncorrelated) and 0.06 to 0.17 (correlated), who find a rate of return about 5%. However, this value is lower than the average estimated rate. The determinants of our model are quite robust across the different model specifications. The output elasticities in the OLS regression for labor and capital are 85.9% and 14.6% respectively.

We conduct few tests designed primarily to ensure the robustness of the sign and significance pattern of our empirical model reported in Table III-1. Table III-1 shows additional results of the R&D production function to assess the robustness of the elasticity of the firm's R&D stock with respect to output. Our primary results of R&D elasticity indicate 4.3% (column 1 of Table III-1). This result is about the same when we use turnover to measure the firm's output (column 2 of Table III-1), the estimated R&D stock elasticity is slightly lower 2.1 %. The output elasticities in the OLS regression for labour and capital are 76.1 % and 20.1% respectively. A second possibility is that the results may reflect differences due to the construction of physical capital. Considering a direct measure of physical capital in place of the constructed physical capital using a perpetual inventory method (column 3) also leads to similar results for the R&D stock elasticity (See Appendix I-3), where the output elasticities in the OLS regression for labor and capital are 85.4% and 16.2%. The quantile regression corroborates the previous findings of other alternative estimation methods.

## Table III-1. R&D elasticity by country level

| | (1) | (2) | (3) | (1) | (2) | (3) | (1) | (2) | (3) | (1) | (2) | (3) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | OLS, robust | OLS, robust | OLS, robust | RE | RE | RE | FE | FE | FE | Quantile | Quantile | Quantile |
| *l* | 0.859*** | 0.760*** | 0.854*** | 0.884*** | 0.728*** | 0.872*** | 0.814*** | 0.636*** | 0.834*** | 0.857*** | 0.761*** | 0.855*** |
| | (0.00427) | (0.00694) | (0.00452) | (0.00503) | (0.00695) | (0.00531) | (0.00692) | (0.00808) | (0.00698) | (0.00321) | (0.00576) | (0.00330) |
| *c* | 0.146*** | 0.201*** | 0.162*** | 0.087*** | 0.083*** | 0.122*** | 0.053*** | 0.055*** | 0.052*** | 0.133*** | 0.199*** | 0.149*** |
| | (0.00285) | (0.00427) | (0.00339) | (0.00272) | (0.00340) | (0.00392) | (0.00314) | (0.00359) | (0.00561) | (0.00201) | (0.00343) | (0.00232) |
| *r&dstock* | 0.043*** | 0.021*** | 0.039*** | 0.040*** | 0.036*** | 0.033*** | 0.022*** | 0.017*** | 0.021*** | 0.051*** | 0.025*** | 0.047*** |
| | (0.00196) | (0.00312) | (0.00198) | (0.00328) | (0.00450) | (0.00338) | (0.00501) | (0.00557) | (0.00529) | (0.00179) | (0.00297) | (0.00178) |
| *Year Dummies* | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| *Industry Dummies* | yes | yes | yes | yes | yes | yes | no | no | no | yes | yes | yes |
| *R-squared* | 0.914 | 0.811 | 0.912 | 0.911 | 0.799 | 0.911 | 0.885 | 0.782 | 0.883 | - | - | - |
| *Pseudo $R_2$* | - | - | - | - | - | - | - | - | - | 0.742 | 0.588 | 0.739 |
| *Prob > F* | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | - | - | - |
| *N(number of firm-year observations)* | 29553 | 20988 | 29392 | 29553 | 20988 | 29392 | 29553 | 20988 | 29392 | 29553 | 20988 | 29392 |

Notes:

(1) With value added

(2) With turnover

(3) With value added and new constructed physical capital (see Appendix I-3).

Dependent variable: logarithm of value added growth 2000-2013 (y);

* significant at the 10% level of significance;

** significant at the 5% level of significance;

*** significant at the 1% level of significance.

RE – Random Effects; FE – Fixed Effects.

The Hausman test indicated the positive results in favour of fixed effects model.

### 3.5.2 Regional level

This section tests the regional differences in Belgium. Table III-2 reports the results from the regressions examining whether there is any regional differences on growth performance in terms of value added. With respect to the regional differences, the Flemish Region reaches the highest rate of return to R&D stock (4.4%), whilst the Brussels-Capital Region shows slightly lower R&D elasticities (4.3%) with the Walloon Region (3.6%). Capron and Meeusen (2000) test the distribution of the R&D productivity by regions in Belgium measured by the ratio of patents on R&D expenditure. The results demonstrate regional differences when companies are performing R&D activities. In our case the results vary slightly between regions which can be explained by a catching up process associated with a smaller technical gap between regions compared to ten years ago. According to the output, the Flemish Region performs better than the Walloon Region, which can be explained by historical factors and insufficient industrial base in the Walloon Region. The Flemish Region is characterized by the highest effects of R&D stock and patent activity. The Brussels-Capital Region demonstrates good indicators of business R&D and low output indicators, which can be explained by the fact that researchers who work in Brussels, live in the Flemish Region or in the Walloon Region. The Brussels-Capital is characterized as networking and metropolitan city, where nearby partners can benefit from the dynamic synergies of interactive growth via reciprocity and knowledge exchange (Batten, 1995). As stated in the work of Jacobs (1969, 1984) a metropolitan region provides a firm both accessibility to local and regional knowledge sources and greater opportunities to access global knowledge sources than other regions provide.

In Table III-2 we present additional results (column 2 of Table III-2) of the R&D production function to assess the robustness of the firm's R&D stock elasticities with respect to output growth among Belgian regions. The primary results of R&D elasticities (column 1 of Table III-2), with using the value added as the output growth, indicates 4.3% in the Brussels-Capital Region whilst using turnover as the output growth shows similar R&D elasticities (2.4%) in the same region. Analogous results we observe with the Flemish and Walloon Regions, the R&D elasticities are in line. In Map 2 we illustrate R&D elasticities by Belgian regions geographically.

Finally, fixed effects model where the unobserved firm-effect are permitted to be correlated with the regressors, and random effects model that assumes that the firm is purely random and uncorrelated with the regressors are estimated (see Appendix I-4, Table 4.1). Looking then at the fixed effects (FE) and random effects (RE) estimates, two different results emerge. The fixed effect regression shows no correlation between regions and firm productivity. In contrast, the coefficient estimates are highly significant and similar to the OLS-estimates in the RE-estimation. The Hausman test rejects the null hypothesis that the RE estimator is consistent. The unobserved firm-specific effects do appear to be correlated with the regressors, which means that they are endogenous, and the FE is a more appropriate estimator. However, we should not automatically interpret a rejection of the null hypothesis in a Hausman test as a rejection of the RE-model as an adaption of the FE model, since there are very strong assumptions underlying the test (Baltagi, 2008).

**Table III-2. R&D elasticity by regions**

| Variable | Regions | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (1) | (2) | (1) | (2) |
| | Brussels-Capital Region | Brussels-Capital Region | Flemish Region | Flemish Region | Walloon Region | Walloon Region |
| *l* | 0.889*** | 0.792*** | 0.823*** | 0.726*** | 0.898*** | 0.757*** |
| | (0.0130) | (0.0215) | (0.00535) | (0.00859) | (0.00832) | (0.0140) |
| *c* | 0.148*** | 0.176*** | 0.157*** | 0.208*** | 0.124*** | 0.222*** |
| | (0.00867) | (0.0123) | (0.00341) | (0.00513) | (0.00564) | (0.00929) |
| *r&dstock* | 0.043*** | 0.024** | 0.044*** | 0.026*** | 0.036*** | 0.016** |
| | (0.00637) | (0.0104) | (0.00234) | (0.00358) | (0.00407) | (0.00664) |
| *Year Dummies* | yes | yes | yes | yes | yes | yes |
| *Industry Dummies* | yes | yes | yes | yes | yes | yes |
| $R_2$ | 0.937 | 0.846 | 0.908 | 0.789 | 0.916 | 0.845 |
| *Prob > F* | 0 | 0 | 0 | 0 | 0 | 0 |
| *N(number of firm-year observations)* | 2819 | 2089 | 19325 | 13974 | 7392 | 4914 |

Notes:

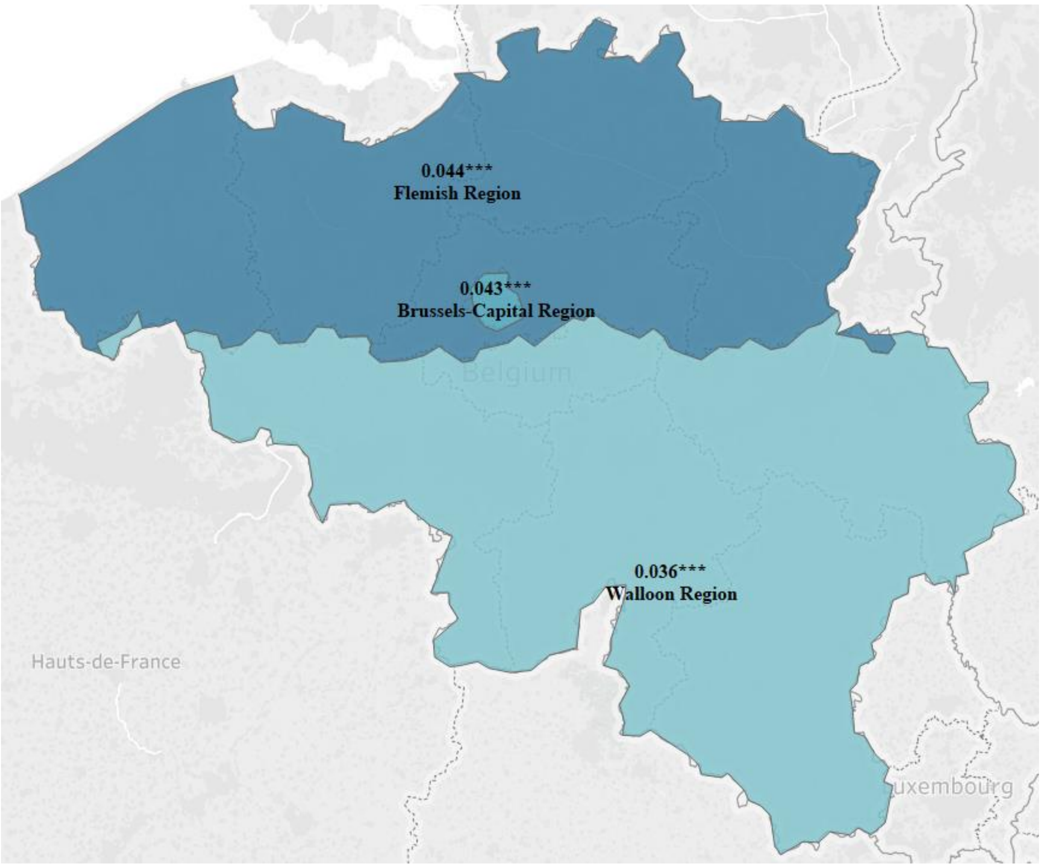
(1) With value added

(2) With turnover

Dependent variable: logarithm of value added growth 2000-2013 (y);* significant at the 10% level of significance;** significant at the 5% level of significance;*** significant at the 1% level of significance.

The Hausman test indicated the positive results in favour of fixed effects model.

## Map 2. R&D elasticity by region




Source: Tableau software, own elaboration

### 3.5.3 Provincial level

In this section we explore if there are any provincial differences on growth performance in terms of value added. Table III-3 provides information on R&D elasticities of eleven Belgian provinces.

As in previous tables, the dependent variable is output growth, in terms of value added (and measured in natural logarithms). The results in Table III-3 introduce the rates of return to R&D stock in Belgian provinces. The empirical outcome points to the presence of provincial disparities in Belgium. The rate of return to R&D stock varies among Belgian provinces for the period 2000-2013. The Brussels province reaches the highest rate of return to R&D stock (nearly 4.3%) whilst Antwerp, Flemish Brabant, Walloon Brabant, West Flanders and East Flanders provinces show rather similar R&D elasticities. Companies like BASF, Agfa Gevaert, Borealis and Solvay mainly located in the area around. Teirlinck & Spithoven, (BELSPO) state that these provinces together are the most attractive for large spending high-tech R&D firms active in ICT and telecommunication (Philips, Siemens, Alcatel Bell), chemicals and pharmaceuticals (Janssen Pharmaceutica, GlaxoSmithKline, Agfa-Gevaert, UCB and Exxon Mobile).

Positive and significant results also emerge from the Hainaut, Liege, Limburg and Namur provinces. The Luxembourg province shows the weakest performance because of the insignificance of their coefficients with respect to the rates of return to R&D stock. This might be due to the high human resources in science and technology, but comparatively low R&D spending. According to the private R&D expenditures Luxembourg relies upon a small number of companies. In the statistical compendium by Teirlinck & Spithoven, the authors are focusing on the evolution in provincial business R&D activities. Their interests are fostered by the idea that small geographical areas often possess particularities in strengths and weaknesses, opportunities and threats in terms of R&D and innovation. Teirlinck & Spithoven states that business R&D activities for the period 1992-2001 did not turn out to decrease in terms of R&D budgets during the past decade. The authors find persisting heterogeneity of the R&D performance at the provincial level. The results show that policies developed to stimulate regional equity in economic terms were not very successful.

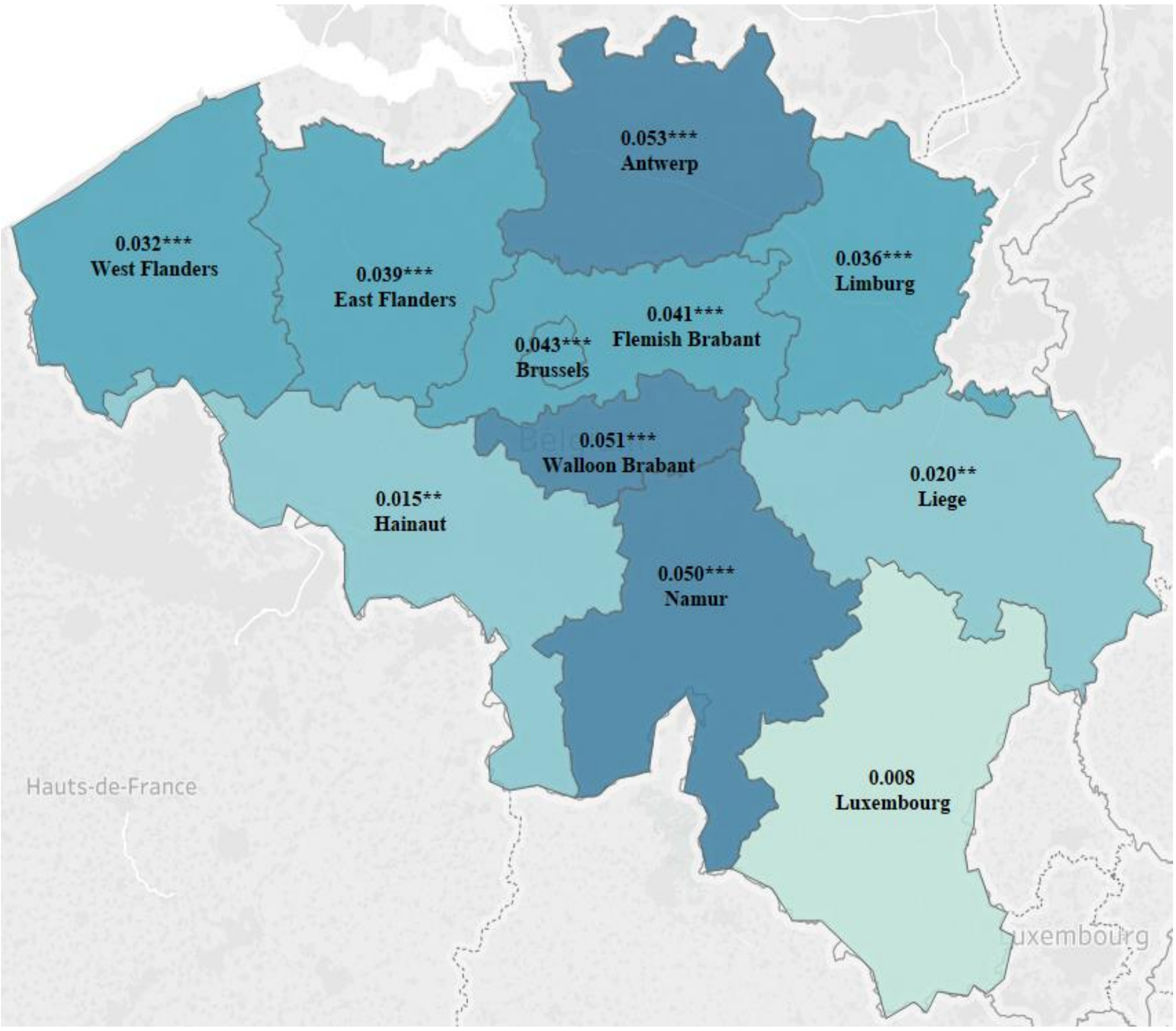
Additionally, Table III-3 includes alternative estimation method, where we comprise the total sales as the output growth (column 2 in Table III-3). The primary results of R&D elasticity, with using the value added as the output growth (column 1), indicate only one province with nonsignificant results. The level of significance of R&D elasticity for some provinces is changing with applying the turnover as the output growth. Here we observe nonsignificant elasticities for the Flemish Brabant, Walloon Brabant, West Flanders, Hainaut, Liege and Namur provinces. One possible explanation of such outcome is due to sensitivity of results to missing values in our company survey data. Map 6 illustrates R&D elasticities by Belgian provinces geographically.

## Table III-3. R&D elasticity by province

| Coefficient | Province | | | | | |
|---|---|---|---|---|---|---|
| | l | *c* | *r&dstock* | *R-squared* | *N(number of firm-year observations)* | *Prob > F* |
| ANTWERP | 0.807*** | 0.169*** | 0.053*** | 0.921 | 4787 | 0 |
| | (0.0109) | (0.00687) | (0.00451) | | | |
| BRUSSELS | 0.889*** | 0.148*** | 0.043*** | 0.937 | 2819 | 0 |
| | (0.0130) | (0.00867) | (0.00637) | | | |
| FLEMISH BRABANT | 0.903*** | 0.112*** | 0.039*** | 0.911 | 2889 | 0 |
| | (0.0125) | (0.00844) | (0.00611) | | | |
| WALLOON BRABANT | 0.987*** | 0.072*** | 0.041*** | 0.917 | 1326 | 0 |
| | (0.0240) | (0.0135) | (0.0105) | | | |
| WEST FLANDERS | 0.784*** | 0.166*** | 0.032*** | 0.914 | 4365 | 0 |
| | (0.0107) | (0.00689) | (0.00411) | | | |
| EAST FLANDERS | 0.813*** | 0.143*** | 0.051*** | 0.902 | 4761 | 0 |
| | (0.0104) | (0.00595) | (0.00465) | | | |
| HAINAUT | 0.879*** | 0.137*** | 0.020** | 0.913 | 2311 | 0 |
| | (0.0156) | (0.00918) | (0.00800) | | | |
| LIEGE | 0.892*** | 0.129*** | 0.036*** | 0.922 | 2646 | 0 |
| | (0.0137) | (0.00983) | (0.00658) | | | |
| LIMBURG | 0.839*** | 0.182*** | 0.0146** | 0.912 | 2523 | 0 |
| | (0.0157) | (0.00913) | (0.00694) | | | |
| LUXEMBOURG | 0.968*** | 0.044** | 0.008 | 0.941 | 220 | 0 |
| | (0.0309) | (0.0204) | (0.0175) | | | |
| NAMUR | 0.888*** | 0.104*** | 0.050*** | 0.933 | 889 | 0 |
| | (0.0181) | (0.0147) | (0.00980) | | | |
| *Year Dummies* | yes | | | | | |
| *Industry Dummies* | yes | | | | | |

Notes:
Dependent variable: logarithm of value added growth 2000-2013 (y);
* significant at the 10% level of significance;
** significant at the 5% level of significance;
*** significant at the 1% level of significance.
see Appendix I-4, Table 4.2A for a robustness check with dependant variable expressed as logarithm of turnover growth and 4.2 for Fixed and Random effects estimates.

**Map 3. R&D elasticity by province**



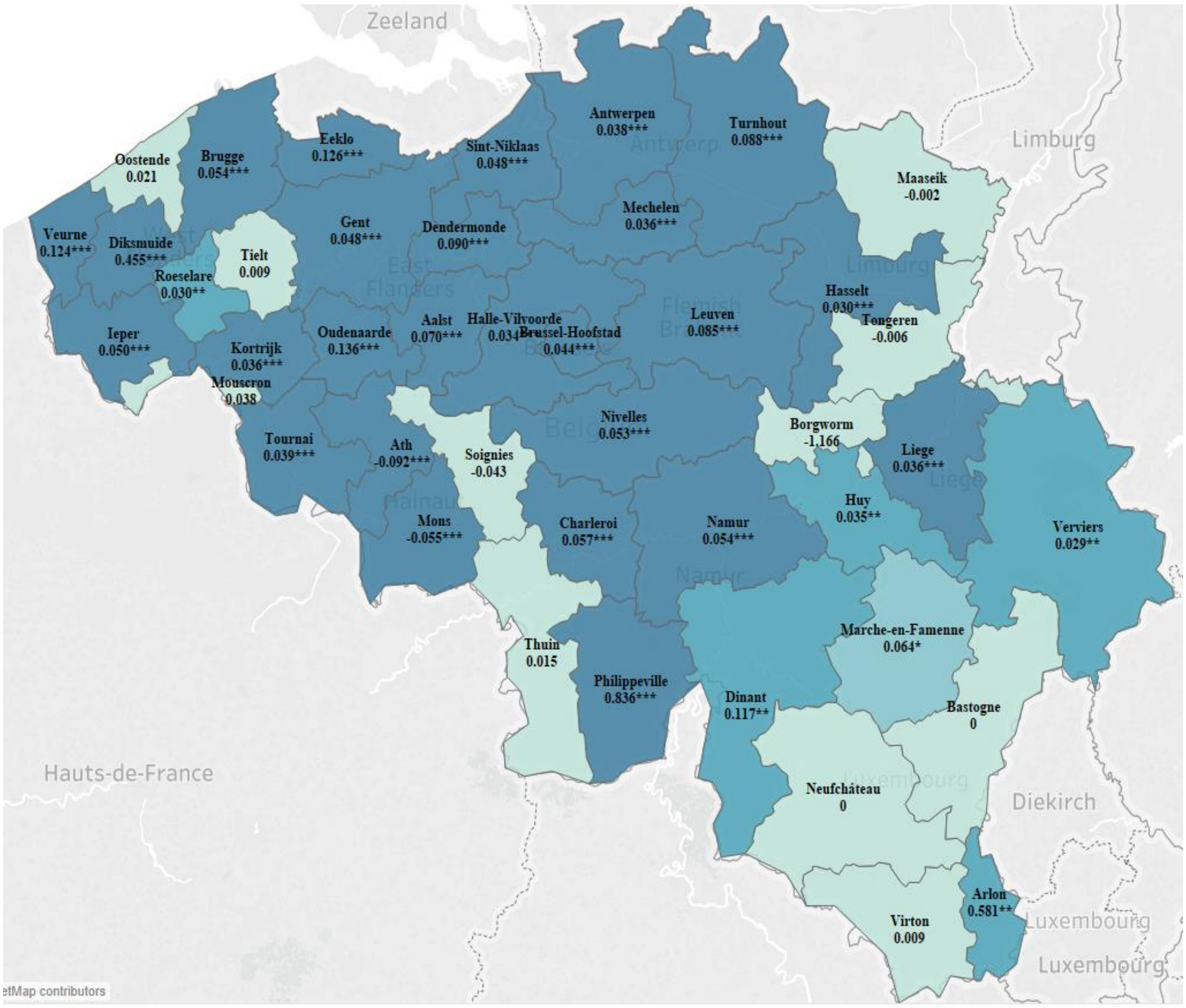

Source: Tableau software, own elaboration

- -non-significant outcome
- - significant at the 5% level of significance;
- - significant at the 1% level of significance, elasticities between 0.032-0.043;
- - significant at the 1% level of significance, elasticities < 0.050.

## 3.5.4 District level

The analysis aims to identify differences in growth performance in terms of value added base of the district agglomeration level in this Chapter. As can be seen from Map 4 and Appendix I-5, the rates of return to R&D stock differentiate across Belgian districts.

**Map 4. R&D elasticity by district**




Source: Tableau software, own elaboration

- -non-significant outcome
- - significant at the 10% level of significance;
- - significant at the 5% level of significance;
- - significant at the 1% level of significance.

Map 4 explores the impact of different Belgian districts on output growth. At the district level the OLS regression points to a significant impact on output growth in 32 districts, however, 11 districts do not show any significance, such results can be influenced by the luck or absence of the needed number of observations for several districts. The outcome shows that 5 districts out of 43 perform R&D elasticities smaller than 1% level of significance. The Philippeville and Diksmuide districts indicate the highest R&D elasticity. Positive and significant effect of output growth indicates such districts as Aalst, Ghent, Saint-Nicolas and Dendermonde which belongs to the East Flanders province. The West Flanders province also reveals some districts with positive and significant effect in the growth of value added: Bruge, Kortrijk and Ipres. Considering the Antwerp province, we identified few districts with significant influence on output growth such as Antwerp, Mechelen and Turnhout districts. The other group with meaningful outcome presented by the Flemish Brabant and Liege provinces which include Halle-Vilvoorde, Leuven districts and Liege and Verviers districts. The highly significant positive values of the respective coefficients indicate that neighbouring districts share some common influences.

### 3.5.5 City agglomeration level

In this section we present the analysis at the level of the Brussels city agglomeration in comparison with the Large and Regional city agglomerations in Belgium. In total, there are three categories of city-regions that are relevant in this study when comparing the Brussels city agglomeration to other agglomeration types. A comparison at city agglomeration level can shed additional light in terms of productivity growth and R&D returns in comparison with the Brussels-Capital Region level. This additional level analysis is relevant because the R&D returns can exert different influence on productivity growth in the Brussels-Capital Region in comparison with the city agglomeration. Table III-4 reports the results from the estimation of the baseline equation according to the city agglomeration level.

The elasticities of R&D stock for the Brussels city agglomeration indicates towards a positive and significant influence on output in terms of value added growth (y), with a rate of return to R&D stock of 4.1%. The output elasticities in the OLS regression for labor and capital are 87% and 15.1% respectively. The Large city agglomerations reach higher rate of return to R&D stock (4.2%), while the Regional city agglomeration indicates the lowest rate of return to R&D stock (2.4%). These results confirmed that innovative firms located in large city agglomerations can benefit from innovative capacity in comparison with that firms which are situated in more isolated environments (Cohen and Levinthal, 1990; Gertler, 1995; Baptista and Swann 1998). Fitjar and Rodriguez-Pose (2011) also state that large city agglomerations have a wider diversity of knowledge sharing and bounds repetitive information, which stimulates the development of radical innovations.

The R&D elasticities in the Brussels city agglomeration and the Large city agglomeration exert the highest positive and significant influence on productivity growth. The rate of return to R&D stock in the Brussels city agglomeration does not differ much from those in the Brussels-Capital Region. The results at the level of the Brussels-Capital Region are largely confirmed at city agglomeration level; absence of major differences in the rate of return to R&D stock of Belgian innovative firms. However, the results in our study do not indicate distinctions between the Brussels-Capital region and the Brussels city agglomeration. The findings of Teirlinck and Spithoven (2018) at the Brussels-Capital Region and at Brussels city agglomeration level confirm that particularities of Brussels are not restricted to the Capital Region but can be seen at an overarching Brussels city agglomeration innovation system.

As in previous sections, we include the turnover as the output growth (2). The results show in some cases similar outcome. The Brussels city agglomeration shows the weakest performance because of the insignificance of its coefficient with respect to output elasticities. This might be due to the insufficient amount of observations in the database. The Large city agglomeration indicates slightly lower rate of return to R&D stock (2.2%) than on output in terms of value added growth (4.2%). According to the Regional city agglomeration, the rate of return to R&D stock is negative and significant at 10 % level of significance. Escribano et al. (2009) indicate that the R&D capacity of city-agglomerations is a vital dimension in the R&D knowledge base because it permits localised actors to manage (local and non-local) external information sources more effectively. The importance of a strong regional R&D capacity is also implied by the pan-

European research efforts such as Horizon 2020 which aim to reinforce regional capacities (Miguélez and Moreno 2015).

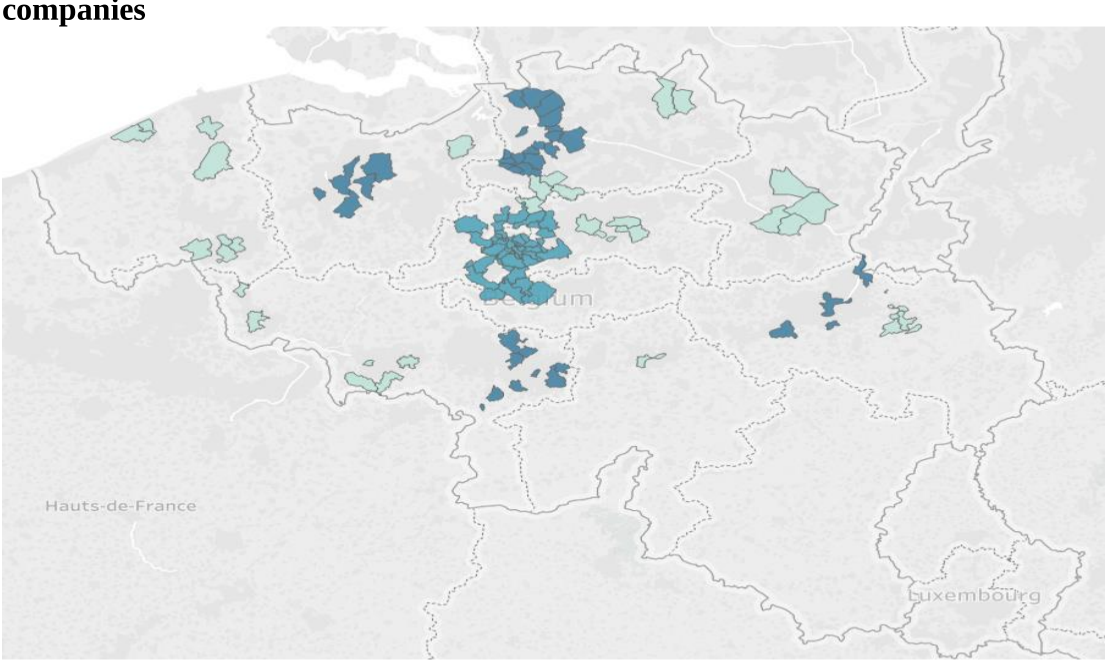
**Table III-4. R&D elasticity by city agglomeration**

| Variable | City agglomeration | | | | | |
|---|---|---|---|---|---|---|
| | Large | | Regional | | Brussels-Capital | |
| | (1) | (2) | (1) | (2) | (1) | (2) |
| *l* | 0.896*** | 0.700*** | 0.866*** | 0.839*** | 0.870*** | 0.812*** |
| | (0.0155) | (0.0279) | (0.0145) | (0.0259) | (0.0175) | (0.0241) |
| *c* | 0.107*** | 0.205*** | 0.142*** | 0.192*** | 0.151*** | 0.174*** |
| | (0.00855) | (0.0148) | (0.00886) | (0.0157) | (0.00994) | (0.0130) |
| *r&dstock* | 0.042*** | 0.022** | 0.024*** | -0.018* | 0.041*** | 0.003 |
| | (0.00538) | (0.0109) | (0.00629) | (0.00977) | (0.00675) | (0.0105) |
| *Year Dummies* | yes | yes | yes | yes | yes | yes |
| *Industry dummies* | yes | yes | yes | yes | yes | yes |
| *R-squared* | 0.910 | 0.813 | 0.916 | 0.829 | 0.923 | 0.826 |
| *Prob > F* | 0 | 0 | 0 | 0 | 0 | 0 |
| *N(number of firm-year observations)* | 1712 | 1410 | 2654 | 2079 | 2433 | 2009 |

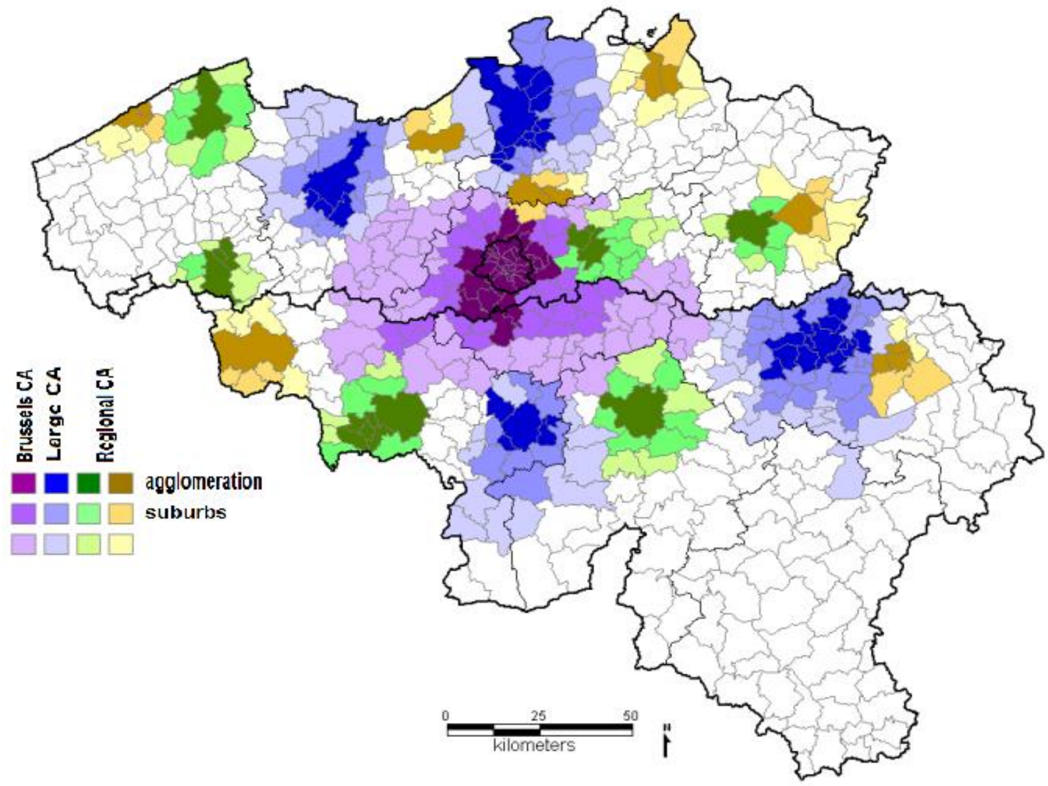
Notes:
(1) With value added
(2) With turnover

Dependent variable: logarithm of value added growth 2000-2013 (y); * significant at the 10% level of significance; ** significant at the 5% level of significance; *** significant at the 1% level of significance.
see Appendix I-4, Table 4.3 for Fixed and Random effects estimates.

**Map 5. R&D elasticity by city agglomeration level, mapping R&D active Belgian companies**



Source: Tableau software, own elaboration
Note: based on the work of Luyten, S., & Van Hecke, E. (2007). De belgische stadsgewesten 2001.



Source: Luyten, S., & Van Hecke, E. (2007). De belgische stadsgewesten 2001.

## 3.6 Robustness check

### 3.6.1 Robustness of the R&D stock elasticity using Two-Step SYSGMM method

We conduct additional test designed primarily to ensure the robustness of the sign and significance pattern of the empirical model reported in Table III-1. We estimated Two-Step SYSGMM (Table III-5). These models also allow one to consider the possible endogeneity or simultaneity issue of the explanatory variables with the error term.

The validity of the set of instruments can be tested through the Sargan or Hansen over-identification tests. The null hypothesis is that the instruments are valid, i.e. they are uncorrelated with the error terms. Under the null hypothesis, the test statistic follows a chi-squared distribution with a number of degrees of freedom being equal to the number of over-identifying restrictions. Rejection of the null hypothesis casts a doubt on the validity of the set of instruments.[z] This suggests that both tests are invalid. This may explain why we observe a somewhat lower elasticity for the physical capital, while for the estimated R&D elasticity a similar finding is observed compared to the benchmark.

**Table III-5. Robustness of the R&D stock elasticity using Two-Step SYSGMM method**

| | Two-Step SYSGMM |
|---|---|
| *L.Value added* | 0.187*** |
| | (0.0221) |
| *Labour (l)* | 0.765*** |
| | (0.0349) |
| *Capital (c)* | 0.043*** |
| | (0.00981) |
| *R&D stock* | 0.047*** |
| | (0.0146) |
| *year* | 0.016*** |
| | (0.00111) |
| *Sargan* | 0.000 |
| *Hansen* | 0.000 |
| *AR(1)* | 0.000 |
| *AR(2)* | 0.188 |
| *N(number of firm-year observations)* | 26168 |

Notes: * significance at 10% level; ** significance at the 5% level; *** significance at 1% level.

The initial-conditions assumption for Two-Step SYSGMM model is the following: the instruments $y_{i,t-2}$, $y_{i,t-3}$, . . . are weakly correlated with the first-differenced lagged dependent variable $\Delta y_{i,t-1}$ when $\lambda \rightarrow 1$. Additional moment conditions for the level model are presented: lagged dependent variable, strictly exogenous or predetermined regressors and endogenous regressors. Further lags for the level model are redundant.

### 3.6.2 Spatial autocorrelation

Our empirical analysis involves the data which contains the location of observations. This data can embed some spatial pattern which might cause a number of measurement problems, known as spatial autocorrelation effects. The spatial autocorrelation appears as observation in spatial proximity is matched by value similarity (Anselin, 1995). For the issue of spatial autocorrelation sophisticated body of specialised techniques have been developed (Griffith, 2013; Halleck & Elhorst, 2015). However, the common issue arises from the quality of data source and its availability at the micro level which is not very common in Europe as in US. In spatial econometrics, there is only one realisation of the data-generating process. If the

[z] One possible explanation of such outcome is due to sensitivity of results to missing values in our company survey data.

observation of the spatial distribution is incomplete (there are missing values), the model cannot be estimated. One solution can be proposed as interpolating the missing values using geostatistical techniques (Anselin 2001). However, this leads to measuring variables with errors or using an appropriate estimate (e.g. EM expectancy-maximisation algorithm, Wang et al. 2013b for the SAR model). However, these solutions are only possible when the percentage of missing values is small. As a result, none of the methods can be applicable to our data base due to large amount of missing values, which causes the main issue in generating a matrix of weights based on the locations.

## 3.7 Conclusion

This chapter focused on the different spatial levels which can be accounted as a factor influences on productivity growth of R&D active firms. R&D performance may significantly vary between different spatial levels. For this reason, R&D activities considered as an appropriate tool to analyse regional economic development and growth as well as spatial inequalities. The EU Member States are often compared with each other, however, the comparison of a small country like Malta or Luxembourg with Germany, the most populous EU Member State, is very difficult. Comparing data at a regional, sub-national or district level is often more meaningful and such an analysis may also highlight potential disparities within countries, regions or districts. The EU's cohesion policy invests in growth and jobs and promotes territorial cooperation. Cohesion policy aims to reduce the disparities that exist between EU regions, promoting a balanced and sustainable pattern of territorial development. The cohesion fund supports those EU Member States whose gross national income (GNI) per inhabitant is less than 90 % of the EU average. The main aim of our analysis is to foster attention on productivity growth of R&D active firms at the smaller spatial levels (provinces, districts, city agglomerations) and highlight the probability of territorial disparities within Belgium. This rstudy can be potentially relevant for the cohesion policy makers.

This chapter examined a micro-level econometric evidence whether the different spatial levels can be accounted as a factor influence on productivity growth of R&D active firms. Besides, the research extends the existing literature in several ways: analysis of a lower spatial levels such as provinces, districts and city agglomerations in order provide a clearer view on a more detailed country profile of Belgium and it's spatial disparities; comparison of obtained results with previous investigations about Belgium and its spatial differences; assessment of the output growth by using the Cobb-Douglas production function model regarding to the different spatial dimensions.

Based on the Cobb-Douglas production function and panel data, the chapter aims at assessing the measurement of the returns to R&D on output growth. Results from the estimation of the baseline equation show a positive and significant impact of R&D stock on output growth, with a rate of return 4%. These results are in line with the literature. Further investigations in terms of regional differences indicate slight variations of R&D rate of returns between regions which can be explained by a catching up process associated with a smaller technical gap between regions compared to ten years ago.

The chapter also investigated the behaviour of R&D active companies regarding provincial level. The empirical outcome points to the presence of provincial disparities in Belgium. The rate of return to R&D stock varies among Belgian provinces for the period 2000-2013. The Brussels province reaches the highest rate of return to R&D stock (nearly 4.3%) whilst Antwerp, Flemish Brabant, Walloon Brabant, West Flanders and East Flanders provinces show rather similar R&D elasticities. Such trends can be explained by industrial specialisation of the provinces, such companies like BASF, Agfa Gevaert, Borealis and Solvay mainly located in the area around.

The performance in terms of district agglomeration level points to a significant impact on output growth in 32 districts, however, 11 districts do not show any significant results. Positive and significant effect of output growth indicates such districts as Aalst, Ghent, Saint-Nicolas and Dendermonde which belongs to the East Flanders province. The West Flanders province also reveals some districts with positive and significant effect in the growth of value added: Bruge, Kortrijk and Ipres. Considering the Antwerp province, we identified few districts with significant influence on output growth such as Antwerp, Mechelen and Turnhout districts. The other group with meaningful outcome presented by the Flemish Brabant and Liege provinces which include Halle-Vilvoorde, Leuven districts and  Liege and Verviers districts. The highly significant positive values of the respective coefficients indicate that neighbouring districts share some common influences.

Finally, we investigated the measurement of the returns to R&D on output growth by city agglomeration level. The elasticities of R&D stock for the Brussels city agglomeration indicates towards a positive and significant influence on output in terms of value added growth. The Large city agglomerations reach higher rate of return to R&D stock (4.2%), while the Regional city agglomeration indicates lower rate of return to R&D stock (2.4%). The rate of return to R&D stock in the Brussels city agglomeration does not differ much from those in the Brussels-Capital Region. The results at the level of the Brussels-Capital Region are largely confirmed at city agglomeration level. However, the results in our study do not indicate distinctions between the Brussels-Capital region and the Brussels city agglomeration. The findings of Teirlinck and Spithoven (2018) at the Brussels-Capital Region and at Brussels city agglomeration level confirm that particularities of Brussels are not restricted to the Capital Region but can be seen at an overarching Brussels city agglomeration innovation system.

One common pattern which seems to be emerging from the analysis is that regional disparities within the country have certainly improved and changed slowly over time. The trends at NUTs 3 and city-agglomeration levels zoom in on territorial specificities and indicted a more visible presence of spatial disparities.

Next steps are to extend the analysis to a benchmarking exercise choosing the cities of metropolitan regions for comparison commonalities, where Brussels with Vienna and Berlin will bring a particular relevance to this research and Cohesion Policy.

## Appendix I

### Appendix I-1 Representativeness of the database

**Table 1.1 Representativeness of the R&D database: R&D expenditure from applied dataset in % of the main science and technology indicator BERD**

| year | R&D expenditure from applied data set, Euro | BERD from OECD, Euro | % |
|---|---|---|---|
| 2000 | 2479.7 | 3588.6 | 69.1 |
| 2001 | 2766.5 | 3921.1 | 70.6 |
| 2002 | 2804.3 | 3662.4 | 76.6 |
| 2003 | 2771.5 | 3607.9 | 76.8 |
| 2004 | 3056.5 | 3731.8 | 81.9 |
| 2005 | 3073.4 | 3775.6 | 81.4 |
| 2006 | 3559.8 | 4105.6 | 86.7 |
| 2007 | 3691.0 | 4420.4 | 83.5 |
| 2008 | 4023.4 | 4650.0 | 86.5 |
| 2009 | 3984.4 | 4574.8 | 87.1 |
| 2010 | 4102.3 | 5027.7 | 81.6 |
| 2011 | 4597.8 | 5613.4 | 81.9 |
| 2012 | 5173.1 | 6149.0 | 84.1 |
| 2013 | 5363.5 | 6356.8 | 84.4 |

In order to estimate that our R&D dataset do not have any systematic difference except for the treatment applied, we produce a comparison of the initial data on R&D expenditure (with cleaned and adopted version to our research) with the main science and technology indicator BERD. According to the Table 1.1, where R&D expenditure compared with the main science and technology indicator BERD, we obtained R&D expenditures above 40%. Such results indicate substantial level of the representativeness of our modified dataset.

### Appendix I-2 Descriptive statistic

**<u>Definition of variables:</u>**

*y:* logarithm of value added/turnover growth between 2000-2013.
*l:* logarithm of labor growth between 2000-2013.
*c:* logarithm of capital growth between 2000-2013.
*r&dstock:* logarithm of R&D capital stocks between 2000-2013, constructed with Perpetual Inventory Method (PIM).
*region*: three Belgian regions (Brussels-Capital, Flemish and Walloon regions).
*province*: eleven Belgian provinces (Antwerp, Brussel, Flemish Brabant, Walloon Brabant, West Flanders, East Flanders, Hainaut, Liege, Limburg, Luxembourg, Namur).
*city_agglomeration:* For the metropolitan city agglomeration level we consider Antwerpen/Antwerp, Liège, Gent and Charleroi while for the regional city agglomeration level we take into account Brugge, Genk, Hasselt, Kortrijk, Leuven, Mechelen, Mons, Namur, Oostende, Sint-Niklaas, Tournai, Turnhout and Verviers.

*districts:* 43 Belgian districts.

Table 2.1 presents some descriptive statistics for the variables used in the regression analyses.

**Table 2.1 Descriptive statistics**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| *y (value added)* | 31955 | 8.035 | 1.847 | 0.018 | 14.853 |
| *y (turnover)* | 22543 | 9.886 | 1.743 | 0.164 | 16.785 |
| *l* | 31583 | 3.783 | 1.559 | 0.693 | 9.892 |
| *c* | 32588 | 7.534 | 2.446 | 0.008 | 17.718 |
| *c (PIM method)* | 31713 | 7.753 | 2.247 | -0.360 | 17.097 |
| *r&dstock* | 32069 | 7.136 | 1.992 | 0.511 | 15.836 |
| *region* | 33707 | 2.151 | 0.582 | 1 | 3 |
| *province* | 33707 | 4.942 | 2.809 | 1 | 11 |
| *districts* | 25672 | 19.090 | 11.632 | 1 | 43 |
| *city_agglomeration* | 7907 | 2.135 | 0.773 | 1 | 3 |

**Table 2.2 Correlation matrix**

| | *y (value added)* | *y (turnover)* | *l* | *c* | *c (PIM method)* | *r&dstock* |
|---|---|---|---|---|---|---|
| *y (value added)* | 1 | | | | | |
| *y (turnover)* | 0.917 | 1 | | | | |
| *l* | 0.928 | 0.868 | 1 | | | |
| *c* | 0.797 | 0.776 | 0.744 | 1 | | |
| *c (PIM method)* | 0.816 | 0.798 | 0.772 | 0.922 | 1 | |
| *r&dstock* | 0.517 | 0.449 | 0.492 | 0.412 | 0.440 | 1 |

**Appendix I-3 Construction of Physical Capital for robustness check**

We also constructed the Physical capital in few steps, using a perpetual inventory method (PIM). Investment in physical capital is presents as the sum of the following financial items: Sales and disposals of tangible fixed assets (8179) + Revaluation surpluses of tangible fixed assets acquired from third parties (8229) - Cancelled depreciation & amounts written down of tangible fixed assets (8309) + Acquisitions of tangible & fixed assets (8169). The net physical capital stock (in constant 2010 EUR) has been computed by applying a perpetual inventory method with a depreciation of 8% per year for all years following the first year for which historic costs data are available:

$$C_{it} = (1-\delta)C_{it-1} + I_{it} \tag{5}$$

where: $C_{it}$ is the stock of physical capital for firm i at time t; $I_{it}$ represents tangible investments in fixed assets deflated by the total gross fixed capital formation deflator at the two digits industry level; and $\delta$ is a rate of depreciation.

The starting value is based on the net book value of tangible fixed capital assets, $C_{i0}$, in the first observation within the sample period, adjusted for previous year's inflation. This value is obtained by multiplying $C_{i0}$, by the ratio of the total gross fixed capital formation deflator at the two digits industry level in the current year by the one AA years ago, where AA is the estimated average age of each firm's physical capital stock. AA is computed as the difference between the year of the firm's creation, DATE, and the year for which the starting value, $C_{i0}$, is available, with a maximum of 16 years if we assume that the full depreciation of physical capital takes 16 years for accounting purposes.

## Appendix I-4 Fixed and random effects models

### Table 4.1 Fixed and random effects models for Belgian regions

| Variable | Regions | | | | | |
|---|---|---|---|---|---|---|
| | Brussels-Capital Region | | Flemish Region | | Walloon Region | |
| | RE | FE | RE | FE | RE | FE |
| *l* | 0.893*** | 0.759*** | 0.870*** | 0.825*** | 0.892*** | 0.808*** |
| | (0.0162) | (0.0222) | (0.00609) | (0.00847) | (0.0106) | (0.0144) |
| *c* | 0.098*** | 0.048*** | 0.090*** | 0.054*** | 0.080*** | 0.056*** |
| | (0.00884) | (0.0105) | (0.00325) | (0.00377) | (0.00584) | (0.00667) |
| *r&dstock* | 0.047*** | 0.02 | 0.037*** | 0.017*** | 0.041*** | 0.035*** |
| | (0.0105) | (0.0166) | (0.00392) | (0.00598) | (0.00693) | (0.0110) |
| *Year Dummies* | yes | yes | yes | yes | yes | yes |
| *Industry dummies* | yes | no | yes | no | yes | no |
| *R-squared* | - | 0.393 | - | 0.441 | - | 0.898 |
| *Pseudo $R_2$* | 0.935 | - | 0.904 | - | 0.915 | - |
| *Prob > F* | 0 | 0 | 0 | 0 | 0 | 0 |
| *N(number of firm-year observations)* | 2819 | 2819 | 19325 | 19325 | 7392 | 7392 |

Notes:
Dependent variable: logarithm of value added growth 2000-2013 (y);
* significant at the 10% level of significance;
** significant at the 5% level of significance;
*** significant at the 1% level of significance.

## Table 4.2 Fixed and random effects models for Belgian provinces

| Coefficient | | Province | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | *l* | *c* | *r&dstock* | *R-squared* | *Pseudo $R_2$* | *N(number of firm-year observations)* | *Prob > F* |
| ANTWERP | RE | 0.849*** | 0.107*** | 0.043*** | | 0.918 | 4787 | 0 |
| | | (0.0119) | (0.00607) | (0.00768) | | | | |
| | FE | 0.788*** | 0.067*** | 0.004 | 0.909 | | 4787 | 0 |
| | | (0.0176) | (0.00718) | (0.0126) | | | | |
| BRUSSELS | RE | 0.893*** | 0.098*** | 0.047*** | | 0.935 | 2819 | 0 |
| | | (0.0162) | (0.00884) | (0.0105) | | | | |
| | FE | 0.759*** | 0.048*** | 0.02 | 0.923 | | 2819 | 0 |
| | | (0.0222) | (0.0105) | (0.0166) | | | | |
| FLEMISH BRABANT | RE | 0.941*** | 0.065*** | 0.021** | | 0.909 | 2889 | 0 |
| | | (0.0160) | (0.00827) | (0.0104) | | | | |
| | FE | 0.878*** | 0.046*** | -0.014 | 0.897 | | 2889 | 0 |
| | | (0.0225) | (0.00930) | (0.0155) | | | | |
| WALLOON BRABANT | RE | 0.908*** | 0.064*** | 0.055*** | | 0.915 | 1326 | 0 |
| | | (0.0242) | (0.0131) | (0.0175) | | | | |
| | FE | 0.800*** | 0.050*** | 0.017 | 0.914 | | 1326 | 0 |
| | | (0.0306) | (0.0147) | (0.0292) | | | | |
| WEST FLANDERS | RE | 0.850*** | 0.104*** | 0.028*** | | 0.910 | 4365 | 0 |
| | | (0.0109) | (0.00636) | (0.00776) | | | | |
| | FE | 0.850*** | 0.073*** | 0.027** | 0.898 | | 4365 | 0 |
| | | (0.0137) | (0.00747) | (0.0121) | | | | |
| EAST FLANDERS | RE | 0.865*** | 0.070*** | 0.051*** | | 0.898 | 4761 | 0 |
| | | (0.0132) | (0.00696) | (0.00790) | | | | |
| | FE | 0.824*** | 0.030*** | 0.044*** | 0.890 | | 4761 | 0 |
| | | (0.0197) | (0.00817) | (0.0125) | | | | |
| HAINAUT | RE | 0.867*** | 0.081*** | 0.027** | | 0.910 | 2311 | 0 |
| | | (0.0197) | (0.0102) | (0.0121) | | | | |
| | FE | 0.754*** | 0.059*** | 0.01 | 0.907 | | 2311 | 0 |
| | | (0.0274) | (0.0115) | (0.0187) | | | | |
| LIEGE | RE | 0.900*** | 0.086*** | 0.044*** | | 0.921 | 2646 | 0 |
| | | (0.0188) | (0.0110) | (0.0112) | | | | |
| | FE | 0.827*** | 0.061*** | 0.058*** | 0.903 | | 2646 | 0 |
| | | (0.0274) | (0.0125) | (0.0175) | | | | |
| LIMBURG | RE | 0.843*** | 0.120*** | 0.0244** | | 0.909 | 2523 | 0 |
| | | (0.0182) | (0.0101) | (0.0106) | | | | |
| | FE | 0.719*** | 0.0694*** | 0.0154 | 0.901 | | 2523 | 0 |
| | | (0.0268) | (0.0121) | (0.0153) | | | | |
| LUXEMBOURG | RE | 1.009*** | 0.012 | 0.01 | | 0.941 | 220 | 0 |
| | | (0.0440) | (0.0335) | (0.0269) | | | | |
| | FE | 1.384*** | -0.063 | 0.09 | 0.898 | | | 0 |
| | | (0.0799) | (0.0498) | (0.101) | | | | |
| NAMUR | RE | 0.844*** | 0.100*** | 0.056*** | | 0.932 | 889 | 0 |
| | | (0.0257) | (0.0159) | (0.0192) | | | | |
| | FE | 0.765*** | 0.086*** | 0.066* | 0.922 | | 889 | 0 |
| | | (0.0356) | (0.0186) | (0.0340) | | | | |
| *Year Dummies* | yes | | | | | | | |
| *Industry Dummies* | yes | | | | | | | |

Notes:
Dependent variable: logarithm of value added growth 2000-2013 (y);
* significant at the 10% level of significance;
** significant at the 5% level of significance;
*** significant at the 1% level of significance.

## Table 4.2A R&D elasticity by province

| Coefficient | Province | | | | | |
|---|---|---|---|---|---|---|
| | l | *c* | *r&dstock* | *R-squared* | *N(number of firm-year observations)* | *Prob > F* |
| ANTWERP | 0.671*** | 0.205*** | 0.041*** | 0.787 | 3555 | 0 |
| | (0.0169) | (0.0101) | (0.00666) | | | |
| BRUSSELS | 0.792*** | 0.176*** | 0.024** | 0.846 | 2089 | 0 |
| | (0.0215) | (0.0123) | (0.0104) | | | |
| FLEMISH BRABANT | 0.848*** | 0.153*** | -0.002 | 0.809 | 2011 | 0 |
| | (0.0213) | (0.0124) | (0.00902) | | | |
| WALLOON BRABANT | 0.897*** | 0.156*** | 0.014 | 0.844 | 894 | 0 |
| | (0.0405) | (0.0221) | (0.0172) | | | |
| WEST FLANDERS | 0.764*** | 0.188*** | 0.001 | 0.804 | 3051 | 0 |
| | (0.0184) | (0.0101) | (0.00676) | | | |
| EAST FLANDERS | 0.684*** | 0.251*** | 0.025*** | 0.796 | 3515 | 0 |
| | (0.0172) | (0.0115) | (0.00817) | | | |
| HAINAUT | 0.699*** | 0.263*** | 0.002 | 0.855 | 1644 | 0 |
| | (0.0216) | (0.0141) | (0.0111) | | | |
| LIEGE | 0.824*** | 0.187*** | -0.0139 | 0.842 | 1691 | 0 |
| | (0.0261) | (0.0181) | (0.0107) | | | |
| LIMBURG | 0.756*** | 0.216*** | 0.032*** | 0.816 | 1842 | 0 |
| | (0.0226) | (0.0135) | (0.0116) | | | |
| LUXEMBOURG | 0.607*** | 0.463*** | 0.040* | 0.922 | 164 | 0 |
| | (0.0471) | (0.0387) | (0.0210) | | | |
| NAMUR | 0.782*** | 0.170*** | -0.008 | 0.890 | 521 | 0 |
| | (0.0352) | (0.0289) | (0.0209) | | | |
| *Year Dummies* | yes | | | | | |
| *Industry Dummies* | yes | | | | | |

Notes:
Dependent variable: logarithm of turnover growth 2000-2013 (y);
* significant at the 10% level of significance;
** significant at the 5% level of significance;
*** significant at the 1% level of significance.

## Table 4.3 Fixed and random effects models for city agglomerations

| Variable | City agglomeration | | | | | |
|---|---|---|---|---|---|---|
| | Large | | Regional | | Brussels-Capital | |
| | RE | FE | RE | FE | RE | FE |
| *l* | 0.963*** | 0.971*** | 0.929*** | 0.912*** | 0.911*** | 0.824*** |
| | (0.0208) | (0.0278) | (0.0156) | (0.0201) | (0.0189) | (0.0252) |
| *c* | 0.063*** | 0.042*** | 0.076*** | 0.048*** | 0.095*** | 0.055*** |
| | (0.0106) | (0.0125) | (0.00771) | (0.00865) | (0.00903) | (0.0105) |
| *r&dstock* | 0.016 | -0.028* | 0.012 | -0.004 | 0.025** | 0.006 |
| | (0.0112) | (0.0169) | (0.00926) | (0.0133) | (0.0104) | (0.0147) |
| *Year Dummies* | yes | yes | yes | yes | yes | yes |
| *Industry dummies* | yes | no | yes | no | yes | no |
| *R-squared* | - | 0.890 | - | 0.904 | - | 0.905 |
| *Pseudo* $R_2$ | 0.906 | - | 0.912 | - | 0.921 | - |
| *Prob > F* | 0 | 0 | 0 | 0 | 0 | 0 |
| *N(number of firm-year observations)* | 1712 | 1712 | 2654 | 2654 | 2433 | 2433 |

Notes:
Dependent variable: logarithm of value added growth 2000-2013 (y);
* significant at the 10% level of significance;
** significant at the 5% level of significance;
*** significant at the 1% level of significance.

## Appendix I-5 R&D elasticity

## Table 5.1 R&D elasticity by district

| Coefficient | | Districts | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | *l* | *c* | *r&dstock* | *$R^2$* | *Pseudo $R^2$* | *N(number of firm-year observations)* | *Prob > F* |
| Alost | OLS | 0.899*** | 0.123*** | 0.070*** | 0.932 | | 458 | 0 |
| | | (0.0307) | (0.0183) | (0.0129) | | | | |
| | RE | 0.981*** | 0.073*** | 0.068*** | | 0.931 | 458 | 0 |
| | | (0.0392) | (0.0227) | (0.0219) | | | | |
| | FE | 1.034*** | 0.057** | 0.114** | 0.626 | | 458 | 0 |
| | | (0.0518) | (0.0261) | (0.0475) | | | | |
| Antwerpen/ Antwerp | OLS | 0.861*** | 0.160*** | 0.038*** | 0.915 | | 1868 | 0 |
| | | (0.0195) | (0.0103) | (0.00663) | | | | |
| | RE | 0.850*** | 0.108*** | 0.036*** | | 0.913 | 1868 | 0 |
| | | (0.0231) | (0.0112) | (0.0122) | | | | |
| | FE | 0.726*** | 0.065*** | -0.017 | 0.899 | | 1868 | 0 |
| | | (0.0317) | (0.0133) | (0.0193) | | | | |
| Arlon | OLS | 0.623*** | 0.052** | 0.581** | 0.902 | | 56 | 0 |
| | | (0.124) | (0.0221) | (0.231) | | | | |
| | RE | insufficient observations | | | - | - | - | - |
| | FE | insufficient observations | | | - | - | - | - |
| Ath | OLS | 0.935*** | 0.312*** | -0.092*** | 0.958 | | 154 | 0 |
| | | (0.0402) | (0.0255) | (0.0179) | | | | |
| | RE | 0.960*** | 0.262*** | -0.100*** | | 0.956 | 154 | 0 |
| | | (0.0553) | (0.0363) | (0.0269) | | | | |
| | FE | 0.579*** | 0.165*** | 0.068 | 0.89 | | 154 | 0 |
| | | (0.116) | (0.0416) | (0.0777) | | | | |
| Audenarde/Oudenaarde | OLS | 0.612*** | -0.003 | 0.136*** | 0.970 | | 109 | 0 |
| | | (0.0252) | (0.0208) | (0.0165) | | | | |
| | RE | 0.612*** | -0.003 | 0.136*** | | 0.970 | 109 | 0 |
| | | (0.0260) | (0.0242) | (0.0222) | | | | |
| | FE | 0.684*** | 0.023 | -0.126 | 0.88 | | 109 | 0 |
| | | (0.0834) | (0.0405) | (0.0818) | | | | |
| Bastogne | OLS | insufficient observations | | | - | - | - | - |
| | RE | insufficient observations | | | - | - | - | - |
| | FE | insufficient observations | | | - | - | - | - |
| Bruges | OLS | 0.820*** | 0.158*** | 0.054*** | 0.916 | | 409 | 0 |
| | | (0.0351) | (0.0261) | (0.0151) | | | | |
| | RE | 1.089*** | 0.058** | -0.016 | | 0.903 | 409 | 0 |
| | | (0.0528) | (0.0273) | (0.0290) | | | | |
| | FE | 1.304*** | 0.031 | -0.086* | | 0.882 | 409 | 0 |
| | | (0.0785) | (0.0296) | (0.0512) | | | | |
| *Year Dummies* | yes | | | | | | | |
| *Industry dummies* | yes | | | | | | | |

Notes:
Dependent variable: logarithm of value added growth 2000-2013 (y); * significant at the 10% level of significance; ** significant at the 5% level of significance; *** significant at the 1% level of significance.

Continuation of Table 5.1

| Coefficient | | Districts | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | *l* | *c* | *r&dstock* | *R2* | *Pseudo R2* | *N(number of firm-year observations)* | *Prob > F* |
| Brussels-Capital | OLS | 0.851*** (0.0182) | 0.162*** (0.0105) | 0.044*** (0.00736) | 0.931 | | 2065 | 0 |
| | RE | 0.910*** (0.0204) | 0.098*** (0.00986) | 0.032** (0.0127) | | 0.928 | 2065 | 0 |
| | FE | 0.829*** (0.0274) | 0.050*** (0.0117) | 0.016 (0.0214) | 0.911 | | 2065 | 0 |
| Charleroi | OLS | 0.823*** (0.0324) | 0.153*** (0.0223) | 0.057*** (0.0132) | 0.915 | | 645 | 0 |
| | RE | 0.798*** (0.0387) | 0.097*** (0.0191) | 0.061** (0.0243) | | 0.913 | 645 | 0 |
| | FE | 0.622*** (0.0549) | 0.075*** (0.0199) | 0.024 (0.0408) | 0.91 | | 645 | 0 |
| Courtrai/Kortrijk | OLS | 0.834*** (0.0187) | 0.136*** (0.0109) | 0.036*** (0.00668) | 0.919 | | 1428 | 0 |
| | RE | 0.898*** (0.0191) | 0.076*** (0.0100) | 0.029** (0.0134) | | 0.915 | 1428 | 0 |
| | FE | 0.901*** (0.0235) | 0.044*** (0.0117) | -0.004 (0.0258) | 0.900 | | 1428 | 0 |
| Dinant | OLS | 0.498*** (0.0800) | 0.405*** (0.0598) | 0.117** (0.0504) | 0.947 | | 85 | 0 |
| | RE | 0.498*** (0.0680) | 0.405*** (0.0565) | 0.117*** (0.0394) | | 0.947 | 85 | 0 |
| | FE | 0.982*** (0.162) | 0.174** (0.0740) | 0.025 (0.0756) | 0.89 | | 85 | 0 |
| Dixmude/ Diksmuide | OLS | 1.595*** (0.339) | -0.251 (0.225) | 0.455*** (0.0779) | 0.971 | | 32 | 0 |
| | RE | insufficient observations | | | - | | - | - |
| | FE | insufficient observations | | | - | | - | - |
| Eecloo/ Eeklo | OLS | 0.778*** (0.138) | 0.158** (0.0652) | 0.126*** (0.0442) | 0.908 | | 133 | 0 |
| | RE | 1.233*** (0.0796) | -0.003 (0.0443) | 0.045 (0.0472) | | 0.874 | 133 | 0 |
| | FE | 1.314*** (0.0879) | 0.011 (0.0465) | 0.054 (0.0511) | 0.877 | | 133 | 0 |
| Furnes/ Veurne | OLS | 1.086*** (0.110) | 0.218*** (0.0658) | 0.124*** (0.0318) | 0.876 | | 134 | 0 |
| | RE | 1.086*** (0.0834) | 0.218*** (0.0489) | 0.124*** (0.0270) | | 0.876 | 134 | 0 |
| | FE | 0.575*** (0.124) | 0.110*** (0.0415) | 0.071* (0.0400) | 0.855 | | 134 | 0 |
| *Year Dummies* | yes | | | | | | | |
| *Industry dummies* | yes | | | | | | | |

Notes:
Dependent variable: logarithm of value added growth 2000-2013 (y);
* significant at the 10% level of significance; ** significant at the 5% level of significance; *** significant at the 1% level of significance.

Continuation of Table 5.1

| Coefficient | | Districts | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | *l* | *c* | *r&dstock* | *$R^2$* | *Pseudo $R^2$* | *N(number of firm-year observations)* | *Prob > F* |
| Gand/Gent | OLS | 0.815*** | 0.144*** | 0.048*** | 0.897 | | 1925 | 0 |
| | | (0.0175) | (0.00957) | (0.00632) | | | | |
| | RE | 0.859*** | 0.064*** | 0.045*** | | 0.890 | 1925 | 0 |
| | | (0.0191) | (0.00955) | (0.0113) | | | | |
| | FE | 0.808*** | 0.020* | 0.016 | 0.874 | | 1925 | 0 |
| | | (0.0241) | (0.0110) | (0.0172) | | | | |
| Hal-Vilvorde/ Halle-Vilvoorde | OLS | 0.914*** | 0.080*** | 0.034*** | 0.882 | | 1187 | 0 |
| | | (0.0200) | (0.0120) | (0.00858) | | | | |
| | RE | 0.872*** | 0.020* | 0.013 | | 0.875 | 1187 | 0 |
| | | (0.0230) | (0.0107) | (0.0125) | | | | |
| | FE | 0.817*** | 0.006 | -0.016 | 0.844 | | 1187 | 0 |
| | | (0.0263) | (0.0112) | (0.0157) | | | | |
| Hasselt | OLS | 0.814*** | 0.182*** | 0.030*** | 0.904 | | 1273 | 0 |
| | | (0.0218) | (0.0130) | (0.00908) | | | | |
| | RE | 0.858*** | 0.127*** | 0.019 | | 0.902 | 1273 | 0 |
| | | (0.0258) | (0.0135) | (0.0121) | | | | |
| | FE | 0.813*** | 0.091*** | 0.005 | 0.892 | | 1273 | 0 |
| | | (0.0373) | (0.0158) | (0.0174) | | | | |
| Huy | OLS | 1.046*** | -0.018 | 0.035** | 0.969 | | 119 | 0 |
| | | (0.0648) | (0.0380) | (0.0161) | | | | |
| | RE | 1.046*** | -0.018 | 0.035** | | 0.969 | 119 | 0 |
| | | (0.0703) | (0.0417) | (0.0176) | | | | |
| | FE | 0.756*** | 0.086 | 0.002 | 0.963 | | 119 | 0 |
| | | (0.150) | (0.0593) | (0.0538) | | | | |
| Liege | OLS | 0.918*** | 0.103*** | 0.036*** | 0.906 | | 1168 | 0 |
| | | (0.0252) | (0.0145) | (0.00856) | | | | |
| | RE | 0.975*** | 0.061*** | 0.025* | | 0.905 | 1168 | 0 |
| | | (0.0295) | (0.0146) | (0.0139) | | | | |
| | FE | 0.961*** | 0.037** | 0.014 | 0.893 | | 1168 | 0 |
| | | (0.0391) | (0.0168) | (0.0225) | | | | |
| Louvain/Louvain | OLS | 0.788*** | 0.136*** | 0.085*** | 0.912 | | 769 | 0 |
| | | (0.0234) | (0.0141) | (0.0109) | | | | |
| | RE | 0.951*** | 0.044*** | 0.038** | | 0.898 | 769 | 0 |
| | | (0.0338) | (0.0153) | (0.0171) | | | | |
| | FE | 0.975*** | 0.015 | -0.038 | 0.839 | | 769 | 0 |
| | | (0.0428) | (0.0167) | (0.0254) | | | | |
| Maaseik | OLS | 0.825*** | 0.180*** | -0.002 | 0.934 | | 547 | 0 |
| | | (0.0199) | (0.0123) | (0.00910) | | | | |
| | RE | 0.788*** | 0.123*** | 0.016 | | 0.930 | 547 | 0 |
| | | (0.0288) | (0.0167) | (0.0162) | | | | |
| | FE | 0.738*** | 0.073*** | 0.016 | 0.907 | | 547 | 0 |
| | | (0.0377) | (0.0205) | (0.0241) | | | | |
| *Year Dummies* | yes | | | | | | | |
| *Industry dummies* | yes | | | | | | | |

Notes:
Dependent variable: logarithm of value added growth 2000-2013 (y);
* significant at the 10% level of significance; ** significant at the 5% level of significance; *** significant at the 1% level of significance.

Continuation of Table 5.1

| Coefficient | Districts | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | *l* | *c* | *r&dstock* | *$R^2$* | *Pseudo $R^2$* | *N(number of firm-year observations)* | *Prob > F* |
| Malines/ Mechelen | OLS | 0.783*** (0.0192) | 0.163*** (0.0118) | 0.036*** (0.0112) | 0.933 | | 911 | 0 |
| | RE | 0.798*** (0.0234) | 0.110*** (0.0123) | 0.049*** (0.0167) | | 0.930 | 911 | 0 |
| | FE | 0.744*** (0.0289) | 0.077*** (0.0144) | 0.042 (0.0260) | 0.93 | | 911 | 0 |
| Marche-en-Famenne | OLS | 0.550*** (0.136) | 0.064 (0.0554) | 0.064* (0.0344) | 0.942 | | 48 | 0 |
| | RE | insufficient observations | | | - | - | - | - |
| | FE | insufficient observations | | | - | - | - | - |
| Mons | OLS | 1.069*** (0.0377) | 0.050*** (0.0181) | -0.055*** (0.0170) | 0.958 | | 225 | 0 |
| | RE | 1.020*** (0.0480) | -0.008 (0.0222) | -0.015 (0.0256) | | 0.952 | 225 | 0 |
| | FE | 0.964*** (0.0604) | -0.034 (0.0265) | 0.033 (0.0339) | 0.934 | | 225 | 0 |
| Mouscron | OLS | 0.770*** (0.0333) | 0.172*** (0.0245) | 0.038 (0.0245) | 0.873 | | 322 | 0 |
| | RE | 0.762*** (0.0441) | 0.083*** (0.0237) | 0.045 (0.0306) | | 0.865 | 322 | 0 |
| | FE | 0.752*** (0.0587) | 0.040 (0.0273) | -0.010 (0.0455) | 0.841 | | 322 | 0 |
| Namur | OLS | 1.066*** (0.0301) | -0.010 (0.0205) | 0.054*** (0.0118) | 0.918 | | 422 | 0 |
| | RE | 0.964*** (0.0409) | 0.045* (0.0262) | 0.049** (0.0235) | | 0.916 | 422 | 0 |
| | FE | 0.877*** (0.0562) | 0.053 (0.0359) | 0.050 (0.0493) | 0.901 | | 422 | 0 |
| Nivelles | OLS | 0.957*** (0.0295) | 0.104*** (0.0151) | 0.053*** (0.0106) | 0.923 | | 942 | 0 |
| | RE | 0.917*** (0.0275) | 0.076*** (0.0138) | 0.039*** (0.0149) | | 0.921 | 942 | 0 |
| | FE | 0.807*** (0.0336) | 0.047*** (0.0153) | -0.011 (0.0201) | 0.905 | | 942 | 0 |
| Ostende/Oostende | OLS | 0.858*** (0.0414) | 0.095*** (0.0335) | 0.021 (0.0223) | 0.958 | | 186 | 0 |
| | RE | 0.773*** (0.0541) | 0.083*** (0.0301) | -0.008 (0.0297) | | 0.955 | 186 | 0 |
| | FE | 0.662*** (0.0676) | 0.042 (0.0334) | -0.051 (0.0592) | 0.923 | | 186 | 0 |
| *Year Dummies* | yes | | | | | | | |
| *Industry dummies* | yes | | | | | | | |

Notes:
Dependent variable: logarithm of value added growth 2000-2013 (y);
* significant at the 10% level of significance; ** significant at the 5% level of significance; *** significant at the 1% level of significance.

Continuation of Table 5.1

| Coefficient | Districts | *l* | *c* | *r&dstock* | *R2* | *Pseudo R2* | *N N(number of firm-year observations)* | *Prob > F* |
|---|---|---|---|---|---|---|---|---|
| Philippeville | OLS | insufficient observations | | | - | - | - | - |
| | RE | insufficient observations | | | - | - | - | - |
| | FE | insufficient observations | | | - | - | - | - |
| Roulers/ Roeselare | OLS | 0.794*** (0.0301) | 0.143*** (0.0146) | 0.030** (0.0120) | 0.893 | | 669 | 0 |
| | RE | 0.911*** (0.0324) | 0.084*** (0.0165) | 0.013 (0.0179) | | 0.889 | 669 | 0 |
| | FE | 0.932*** (0.0384) | 0.058*** (0.0191) | 0.013 (0.0230) | 0.880 | | 669 | 0 |
| Saint-Nicolas | OLS | 0.791*** (0.0461) | 0.177*** (0.0181) | 0.048*** (0.0158) | 0.851 | | 569 | 0 |
| | RE | 0.896*** (0.0446) | 0.066*** (0.0201) | 0.012 (0.0221) | | 0.835 | 569 | 0 |
| | FE | 0.833*** (0.0613) | 0.038* (0.0219) | -0.012 (0.0292) | 0.819 | | 569 | 0 |
| Soignies | OLS | 0.801*** (0.0782) | 0.299*** (0.0422) | -0.043 (0.0318) | 0.830 | | 123 | 0 |
| | RE | 0.890*** (0.173) | 0.069 (0.0615) | -0.078 (0.0926) | | 0.764 | 123 | 0 |
| | FE | 0.762*** (0.213) | 0.012 (0.0652) | -0.342** (0.150) | 0.298 | | 123 | 0 |
| Termonde/ Dendermonde | OLS | 0.728*** (0.0299) | 0.166*** (0.0157) | 0.090*** (0.0169) | 0.904 | | 464 | 0 |
| | RE | 0.761*** (0.0483) | 0.097*** (0.0241) | 0.125*** (0.0215) | | 0.896 | 464 | 0 |
| | FE | 0.767*** (0.0625) | 0.052* (0.0292) | 0.172*** (0.0295) | 0.871 | | 464 | 0 |
| Thuin | OLS | 0.722*** (0.0632) | 0.276*** (0.0667) | 0.015 (0.0389) | 0.956 | | 64 | 0 |
| | RE | insufficient observations | | | - | - | - | - |
| | FE | insufficient observations | | | - | - | - | - |
| Tielt | OLS | 0.762*** (0.0228) | 0.208*** (0.0156) | 0.009 (0.0102) | 0.931 | | 522 | 0 |
| | RE | 0.813*** (0.0317) | 0.135*** (0.0170) | 0.046** (0.0208) | | 0.926 | 522 | 0 |
| | FE | 0.785*** (0.0429) | 0.094*** (0.0195) | 0.079** (0.0307) | 0.914 | | 522 | 0 |
| *Year Dummies* | yes | | | | | | | |
| *Industry dummies* | yes | | | | | | | |

Notes:
Dependent variable: logarithm of value added growth 2000-2013 (y);
* significant at the 10% level of significance; ** significant at the 5% level of significance; *** significant at the 1% level of significance.

Continuation of Table 5.1

| Coefficient | | Districts | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | *l* | *c* | *r&dstock* | *$R_2$* | *Pseudo $R_2$* | *N(number of firm-year observations)* | *Prob > F* |
| Tongres/ Tongeren | OLS | 0.762*** | 0.228*** | -0.006 | 0.907 | | 227 | 0 |
| | | (0.0347) | (0.0283) | (0.0256) | | | | |
| | RE | 0.856*** | 0.094*** | -0.020 | | 0.90 | 227 | 0 |
| | | (0.0492) | (0.0183) | (0.0379) | | | | |
| | FE | 0.706*** | 0.063*** | -0.041 | 0.89 | | 227 | 0 |
| | | (0.0702) | (0.0192) | (0.0489) | | | | |
| Tournai | OLS | 0.760*** | 0.163*** | 0.039*** | 0.959 | | 290 | 0 |
| | | (0.0231) | (0.0131) | (0.0131) | | | | |
| | RE | 0.772*** | 0.119*** | 0.048 | | 0.96 | 290 | 0 |
| | | (0.0348) | (0.0180) | (0.0292) | | | | |
| | FE | 0.726*** | 0.098*** | 0.055 | 0.93 | | 290 | 0 |
| | | (0.0440) | (0.0198) | (0.0446) | | | | |
| Turnhout | OLS | 0.863*** | 0.133*** | 0.088*** | 0.926 | | 1217 | 0 |
| | | (0.0214) | (0.0129) | (0.00851) | | | | |
| | RE | 0.968*** | 0.056*** | 0.064*** | | 0.92 | 1217 | 0 |
| | | (0.0254) | (0.0110) | (0.0142) | | | | |
| | FE | 0.949*** | 0.033*** | 0.021 | 0.91 | | 1217 | 0 |
| | | (0.0342) | (0.0119) | (0.0222) | | | | |
| Verviers | OLS | 0.892*** | 0.135*** | 0.029** | 0.907 | | 607 | 0 |
| | | (0.0252) | (0.0187) | (0.0120) | | | | |
| | RE | 0.854*** | 0.060*** | 0.034* | | 0.90 | 607 | 0 |
| | | (0.0390) | (0.0188) | (0.0194) | | | | |
| | FE | 0.750*** | 0.034* | 0.005 | 0.89 | | 607 | 0 |
| | | (0.0517) | (0.0201) | (0.0314) | | | | |
| Virton | OLS | insufficient observations | | | - | - | - | - |
| | RE | insufficient observations | | | - | - | - | - |
| | FE | insufficient observations | | | - | - | - | - |
| Waremme/ Borgworm | OLS | insufficient observations | | | - | - | - | - |
| | RE | insufficient observations | | | - | - | - | - |
| | FE | insufficient observations | | | - | - | - | - |
| Ypres/ Ieper | OLS | 0.772*** | 0.169*** | 0.050*** | 0.913 | | 338 | 0 |
| | | (0.0282) | (0.0179) | (0.0134) | | | | |
| | RE | 0.788*** | 0.145*** | 0.053** | | 0.912 | 338 | 0 |
| | | (0.0443) | (0.0234) | (0.0216) | | | | |
| | FE | 0.798*** | 0.124*** | 0.048 | 0.905 | | 338 | 0 |
| | | (0.0649) | (0.0330) | (0.0397) | | | | |
| *Year Dummies* | yes | | | | | | | |
| *Industry dummies* | yes | | | | | | | |

Notes:
Dependent variable: logarithm of value added growth 2000-2013 (y);
* significant at the 10% level of significance; ** significant at the 5% level of significance; *** significant at the 1% level of significance.

CHAPTER IV

# ARE COMPANIES WITH SPATIALLY DIVERSIFIED PATENT COLLABORATION NETWORKS MORE PRODUCTIVE? EVIDENCE FROM BELGIUM

This chapter is based on the INNOVIRIS project "Prospective research for Brussels 2014", "Brussels knowledge flows: localised learning and regional knowledge pipelines (BLOCPIPE)", ULB, Belgium.
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## SUMMARY

*Although the literature on the relations between patents and output growth of R&D active companies has been widely investigated, there has been little research with respect to the impact of patent collaboration networks on the output growth of R&D active companies. Integrating theoretical developments from the literature, we propose and test a conceptual framework that allows us to explain to what extent patent collaboration networks affect output growth. Testing the framework by using a constructed company-level dataset for Belgium, the empirical analysis reveals that output growth is significantly influenced by patenting activities and by collaborative relations with respect to patents. The chapter focuses on two distinct spatial levels. First, the spatial reach of the patent collaboration network is considered. The findings show that output growth is higher when collaborative relations are internationally oriented. Second, the regional location of the company shows differences in patenting activity, patent collaboration, and the spatial reach of the patent collaboration network.*

***Keywords***: *output growth, R&D active companies, patent collaboration networks, regional differences, spatial reach*
***JEL Classification:*** *O12, O34, R11*

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## 4.1 Introduction

The creation and use of new knowledge are the primary factors that drive economic growth (Romer 1986; Romer 1990; Grossman and Helpman 1991; Petruzzelli 2011). A wide range of empirical studies indicates that knowledge positively influences technical change and, thereby, economic growth (Varga and Schalk 2004; Plummer and Acs 2005; Acs and Varga 2005). Hall et al. (2005) state that R&D conducted by private companies is considered as an investment activity, the output of which is an intangible asset that can be termed as the company's 'knowledge' stock. New knowledge can be transformed into new products, processes or organisational routines. To create new knowledge, organisations face a decision to perform research and development (R&D), which might involve cooperative relations between innovators. As stated in the literature, important innovations appear in collaborative work between different partners, because of knowledge spillovers and joint learning processes (Grabher 1993; Boschma 2005; Asheim and Gertler 2005).

One common way to study cooperative relations in innovation is through the analysis of patent based indicators. The information contained in patent data has a particular advantage: it is easily accessible, patents which are granted for inventions that meet a certain inventive step and can be allocated directly to more detailed units of analysis, e.g., technical fields, applicants and inventors (Brockhoff 1992; Ernst 1998). The main findings of these studies establish the link that similar attributes among actors or common environments, influence possible collaborations and produce innovations. The necessity to develop new innovations depends not only on in-house R&D activities and stock of knowledge, but also on the ability to use and combine new knowledge developed elsewhere.

Significant effort was made to investigate the nature and the importance of interactions between industry, academia and government. Companies that are collaborating with universities and research centres perform better in terms of the development of new technologies and products. Companies that are collaborating with other companies (customers, suppliers) perform better in terms of increased turnover from improved products (Faems et al. 2005) or influence labour productivity growth (Belderbos et al. 2004).

However, knowledge that leads to innovation depends on a strong regional component (Jaffe et al. 1993; Audretsch and Feldman 1996; Anselin et al. 1997, 2000; Howells 2002; Fritsch and Franke 2004; Pondset al. 2009; Caragliu and Nijkamp 2015). The location of knowledge production and the characteristics of knowledge diffusion become a crucial issue in understanding economic development (Acs et al. 2002). Varga (1999) and Caniëls (2000) state that production of new scientific and technical knowledge has a prevailing tendency to cluster spatially. Essentially, spatial proximity can play an important role in facilitating knowledge flows between actors in a system of innovation.

This chapter is primarily concerned with the following research question: are research active companies with spatially diversified patent collaboration networks performing better in terms of output growth? This chapter extends the existing literature in several ways. First, we focus on identifying all possible co-application relations among patent applications in Belgium, giving a view on a more detailed country profile in terms of patent co-application ties. Second, we analyse the impact of a particular co-application tie among patent applications (company-individual) on output growth of R&D active companies in Belgium. This chapter uses a novel spatial approach to look into the role played by proximate and distant patent collaboration networks among inventors involved in company-individual co-application relations. The spatial reach of the network, therefore, becomes a central topic of the chapter. Since patent collaboration networks involve spatially proximate and/or distant company-individual patent co-application ties, the chapter decomposes this spatial reach into three categories (BE, EU and ROW) allowing for existing overlaps. This enables an identification of a combination of patent collaboration network locations driving output growth. Certain aspects about the information on co-applications in patents have been studied extensively, for others, like the network of collaborations, there is little or practically no information (Giuri and Mariani 2006). Finally, we test regional differences in order to see the willingness of companies and individuals to cooperate on patents and to demonstrate their impact on the spatial reach of the patent collaboration network.

The remainder of the chapter is organised as follows. Section 4.2 presents a summary of the theoretical and empirical evidence on the topics discussed in this chapter. In Section 4.3 the construction of the database is set out in detail and presents the descriptive statistics. Section 4.4 deals with the specification of the empirical framework and presents the analytical results to explore the role of company-individual patent co-application tie with respect to the spatial reach of the collaboration network. In Section 4.5 robustness check is presented. Final remarks and avenues for further research are discussed in Section 4.6.

## 4.2 Regional differences and spatial reach of patent collaboration networks

### 4.2.1 Theoretical background

Using patent information, Jaffe et al. (1993) demonstrated that knowledge spillovers are spatially concentrated. Since then a lot of attention is given to the role of the spatial distribution of knowledge. A decade later, Acs et al. (2002) reconfirm that knowledge and innovations are unequally spread across space. Several empirical studies also highlight the uneven spatial distribution of R&D activities and their networks of partnerships (Hoekman et al. 2013). The key proposition is that R&D collaboration alters the spatial distribution of knowledge, affecting the territorial competitiveness of regions. However, the overlap and relationships with actors outside the region largely remain a black box.

At the beginning of the 2000s the literature on regional innovation systems (Cooke 2004; Asheim and Isaksen 2002) emphasized the facilitation of spatial proximity for sharing tacit knowledge: companies clustered in a region share a common regional culture by means of social and cultural norms. Many comparative case studies investigated the characteristics of successful regions (e.g. Cooke 2004; Wolfe and Gertler 2004) and typologies of regional innovation systems (Cooke,1998; Asheim and Isaksen 2002). These regional innovation systems are predominantly analysed in the context of administrative regions, characterized as an independent ecosystem based on interactive linkages between various types of regional actors (Cooke et al. 1997; Iammarino 2005). More recently, this regional dimension has been supplemented by acknowledging that relevant knowledge increasingly stems from different parts of the world through 'global' pipelines (Bathelt et al. 2004). Additionally, the resource-based view predicts that, when companies are sourcing new knowledge and technology, they will aim to acquire it irrespective of the location (Spithoven and Teirlinck 2015), whether or not enhanced by institutional, cognitive or social proximity (Boschma 2005). The performance in terms of output growth is expected to differ substantially according to the region in which the company is located.

Bell and Zaheer (2007) posit that knowledge is sourced from other organisations and from different spatial levels via collaborative networks. They, first, put forward that there is not much known about the different types of ties, claiming that linkages involving individuals are superior to others, irrespective of the spatial reach. Second, they emphasize that the regional context itself remains crucial for the existence of collaborative networks.

Regional innovation systems are in place if interacting knowledge exploration and exploitation subsystems are linked to knowledge pipelines outside the region (Cooke et al. 2007). Wanzenböck et al. (2014) find regional differences in knowledge networks, including co-patenting, using social network analysis. These differences are attributed to technology-related elements and spatial spillover effects which characterize regions.

Sources for knowledge refer to external ideas nurturing the company’s knowledge pipeline and can be linked to differences ‘global pipelines’ for innovation (Bathelt et al. 2004). Pipelines refer to “channels of communication used in distant interaction, between companies in clusters and sources of knowledge located at a distance” (Wolfe and Gertler 2004, p.1078). However, empirical insights on these issues in terms of measurement and analysis is still limited.

Current insights focus on regions combining regional with interregional interactions (Bathelt et al. 2004; Maskell et al. 2006; Wolfe and Gertler 2004). Fitjar and Rodriguez-Pose (2011) highlight the absence of a representative quantitative database to measure global pipelines. They also highlight the difficulties in understanding and measuring these global pipelines as a shortcoming in the literature. The accessibility to pipelines depends on the regional location and on industry specificities enabling to bypass the regional environment and set up extra-regional connections (Fitjar and Rodriguez-Pose 2011). Tötdling and Grillitsch (2014) report strong sector differences among 15 case studies in Europe on regional differences in knowledge sourcing patterns and innovation behaviour of companies.

Much of the research on collaboration emphasises that spatial distance matters (Nachum and Zaheer, 2005; Ambos and Ambos, 2009; Cantwell, 2009; von Proff and Brenner, 2014). Spatial distance is identified as an important mechanism for the transfer of knowledge (Kogut and Zander, 1993). Collaboration between companies can have several advantages namely: cost savings, improved decision making, increased revenue through sharing of expertise etc. (Hansen & Nohria, 2004). Storper & Venables (2004) point out, that spatial proximity improves information flows by recombining knowledge and transferring best practices. The authors confirmed that smaller geographic distance can increase collaboration, because of the need for face-to-face communication, where the tacit knowledge can be shared between partners. Zaheer and Manrakhan (2001) confirm that large distances between partners carries expenses for investments. In short, the preferred partners for collaboration will be located the closest to the firm because of the arguments cited above. However, other authors stress that distance does not play a pivotal role anymore, where the transmission of knowledge diminishes with physical distance (Johnson et al., 2002). Johnson at al., (2006) confirmed that the pull of localized knowledge measured through patent citation has weakened remarkably, slowly diminishing with time.

Patenting is often done in collaboration with other inventors to combine additional knowledge. The network of co-inventions can appear within a formal agreement or inventors can choose to collaborate informally with colleagues from different areas. The co-inventor network is thus affected by geographical location of the partners, as spatial proximity and location may contribute to the transfer of more sophisticated knowledge, as well as regular face-to-face interactions are essential. In the empirical work of Cassi and Plunket (2015), the authors strengthen the theoretical considerations that inventors belonging to private sector collaborate over larger distances than academic ones. Regional collaboration is a dominated type of collaboration between inventors, as spatial proximity fosters most other types of proximity and facilitates trust between co-inventors. However, international collaboration is the least considerable. The importance of spatial distance is also stressed by Maggioni et al.(2007). The authors estimated a spatial knowledge production function from aggregated data at a NUTS2 level. Their results indicated that the regional propensity to patent benefits more from local knowledge spillovers than from those resulting from distant collaborations.

The proposed research responds to the following gaps in the literature: (i) provision of a special type of patent collaboration involving companies and individuals, thus adding to the debate on boundary spanning in regional innovation systems; and (ii) provision of original data for patent collaboration in research active companies with attention to knowledge pipelines between companies and individuals; and (iii) introducing a novel approach by including the spatial reach of patent collaboration networks.

### 4.2.2 Empirical insights

While the discussion above suggests much about the spatial distribution of knowledge, little has been mentioned about the relationship between output growth and R&D inputs. For a long time, economists have been developing various methods to estimate the rate of returns to R&D. The main approach often relates the growth of total factor productivity (TFP) to R&D. For that reason, we will review the main empirical findings on R&D and productivity performance.

Most of the research that measures the returns to R&D (the micro or macro levels) relies on a production function framework, where the output is related to the stock of R&D (or knowledge capital). In the work of Hall et al. (2010) the authors conclude that R&D rates of return in developed economies have been strongly positive during the past half century, as well as the estimates based on industry-levels or company-level data. The differences in changes in R&D elasticities can be divided into two streams of literature. The first belongs to the scholars who`s research is based on US companies at the meso economic level, and the second part represent the scholars who produced their research based on European companies or meso economic data. This distinction is covered in the Chapter 3.3.3.

Another important driver of productivity performance is patent activity. Patent statistics stand out as an easily available source and are by definition related to inventiveness. “Something interesting might be learned from such data, which can be rediscovered in each generation" (Griliches 1990). Patents, as an indicator of the innovation process, have attracted much attention in empirical research on various levels: countries, sectors of industry, technologies or companies (Pavitt 1988). Existing empirical studies showed a positive correlation between patents and economic growth, rendering a significant impact on empirical research and business performance. Having more patents influence the economic results of R&D activities, the more significant they become as an output indicator of R&D activities (Griliches 1990; Ernst 1995).

According to Scherer (1965), analysing the inventive output (i.e. patents), profitability, and sales growth in 448 companies in 1955, the growth of corporate profits is positively correlated with inventive output via sales increase. The study of Griliches et al. (1991) looks if there is additional information in patent numbers on the rate and output of inventive activity, above and beyond what is already contained in R&D expenditure data. They provide evidence that there is no influence of unexpected patent applications. The present and past patent applications explain only 5% of the variance in market value change, whilst the number of current patent applications would account for less than 0.1 percent of the total variance.

In a similar vein, the empirical analysis underlines that 'importance' of company's patents have a positive impact on the market value in terms of output growth. This argument is forcefully stated by Austin (1995) where key patents (weighted patents by quality indicator) indicate a stronger impact on output growth. Another, similar, example provided by Ernst (1995), who presents evidence that companies with high quality patents perform better than companies with low quality patents. In addition, the author states that companies which pursue a systematic patent strategy are more thriving. Hall et al. (2005), state that if a company's 'quality' of patents increases - so that, on average, these patents receive one additional citation - the company's market value would increase by 3 %. The other interesting finding of this research indicates that market value is positively correlated with the share of self-citations out of total citations to a company's patents, which depends on the size of the company's patent portfolio.

In summary, from the above considerations we have learned that the rates of return to R&D are positive in many countries: R&D inputs and patents exert a positive and significant influence on productivity growth. Our contribution to this debate is not merely to replicate measurement of the returns to R&D, but to supplement it by including the spatial reach of patent collaboration networks and its impact on output growth.

## 4.3 Data and estimation strategy

### 4.3.1 Database construction

The dataset consists of a representative sample of R&D performing companies in Belgium over the period 2000–2013. The primary data are drawn from the bi-annual R&D survey, organised by the regions in Belgium and compiled by the Belgian Science Policy Office (BELSPO). These longitudinal unbalanced datasets record the R&D expenditure for the period 2000-2013 and contains 7,652 companies. The survey provides information on companies' in-house R&D expenditure. These data are matched with financial data covering net added value, physical capital, employment and sector (NACEBEL codes) from BELFIRST (99% are matched).

BELFIRST gathers detailed information on companies in Belgium (2000-2013). All monetary variables, expressed in current prices, are transformed in constant prices using the GDP deflator (base=2010). To render the database balanced and applicable for construction other variables such as R&D stock, we consider only companies which have R&D expenditure data for five subsequent years. All companies with no R&D data for at least five subsequent years are removed. Further, all extreme values of 1% for the ratio added value to average employment are also removed as these observations might refer to errors. As a result, we obtain a database of 3,686 companies (see Appendix II-1 on the representativeness of the database). Further, for each year, these R&D data are matched with patent data using the common names of the companies.

The use of patent data calls for special attention. Broadly speaking, patents represent one of the most used indicators to study the impact of inventiveness on the economic environment and to trace the interactions and technology flows across sectors, countries, cities and companies. A patent is an intellectual property right that gives its owner the exclusive right to use his/her invention in a particular technological field for a limited number of years (in general 20 years). The information is retrieved from the PATSTAT raw data which contains inventor information with country and city names and applicant information (version 14.24 PATSTAT Biblio, Edition 2016 - Autumn). PATSTAT contains bibliographical information and the legal status of patent documents granted in more than 100 patent offices worldwide. The information contained in the PATSTAT is presented through a set of tables that follow a relational database structure where tables can be differently connected to each other in order to get necessary information by using relevant entry keys. The tables in the PATSTAT database contain information on each patent application, e.g., inventors and owners, technology fields, titles and abstracts, publication dates and citations, names, addresses, countries of applicants or inventors. As a search engine we used the country name – Belgium – where at least one assignee is located in Belgium. The datamining process required three steps.

First, all patent data have at least one assignee from Belgium and contain the following information: application identifier, person name, person address, sequence number of inventors, sequence number of applicant (number indicating the place in the list of applicants in the application). In the second step the applicant information data contains the application identifier and the harmonized applicant name[27], type of organisation (i.e. applicants may have been assigned to one or more organisation type, such as company, government or non-profit organisation, university or hospital) and Person country code (country part of the correspondence address of the person or business). Third, the inventor data are merged with the applicant information using the application identifier. Hence, it becomes necessary to identify only the first filled patent application in order to exclude duplicates within the same family group. This means that one patent application could be registered in several patent offices and in PATSTAT can be recognised through different application identifiers. Nonetheless, this patent application belongs only to one patent family. To avoid overlap, the application identifier and application identifier of the earliest filing are compared, the comparison shows the first filled patent application among patent family and exclude

[27] This harmonization of applicants' names comes from the HAN patent database released by the OECD (2016); http://www.oecd.org/sti/innovationinsciencetechnologyandindustry/oecdpatentdatabases.htm

duplicates within the same family group. As a result, the total number of first applied patent applications amounted to 32,834 original patent applications covering the period 1995-2013. In addition, all patents are dropped where the type of organisation – company, government organisation, non-profit organisation, university or hospital – could not be identified after additional cleaning and where the names of different organisations which are missing. For the 2000-2013 period the total number of observations dropped to 24,629 patent applications, but no implications for the representativeness of the data or the analysis has been found.

Some issues with patent data are detected during its processing. First, identification of the type of organisation is not always correct in the original patent dataset. If the organisation of an applicant could not be determined, then the organisation is classified as unknown. Every organisation is manually checked. Second, names of the same organisations can have different spellings which are identified through manual cleaning. Special attention is given to the universities, because 'KULeuven' and 'UCL' are sometimes incorrectly identified due to the use of the same (English) name.

Further, in Figure IV-1 we explain next steps for obtaining the final version of the patent database. First, the patent co-application ties between different organisations among applicants are identified. The results show that 14.6 % of all patent applicants are the result of co-application relations (i.e. 3,585 patent co-applications among 24,629 patent applications). Similar results are found in the study of Capron et al. (1998), where on average 10 % of patents are co-applied patent applications (EPO patents over the period 1978-1994). Furthermore, 50 co-applied patent ties between different organisations could be distinguished (see Appendix II-2). The top five co-application relations are shown in Figure IV-1. According to Figure IV-1, the most co-applied patent applications occur mainly between companies and individuals (63.2%). Over 20% of individuals co-apply with other individuals when developing a patent. Only 5.2% domestic companies co-apply with foreign companies on patents. The number of co-patents between firms and universities and public research organisations indicates less then 1%. It is very common that the firms tend to cooperate more with other companies than with universities for example. Fritsch and Lukas (2001) analyse 1,800 German companies, where 33% of companies do cooperate with public research centres, 60% with customers, 49% with suppliers and 31% with other companies.

Therefore, based on Figure IV-1, the focus in this chapter lies on company-individual co-application tie among patent applications for the period 2000-2013. In total 2,264 observations are examined.

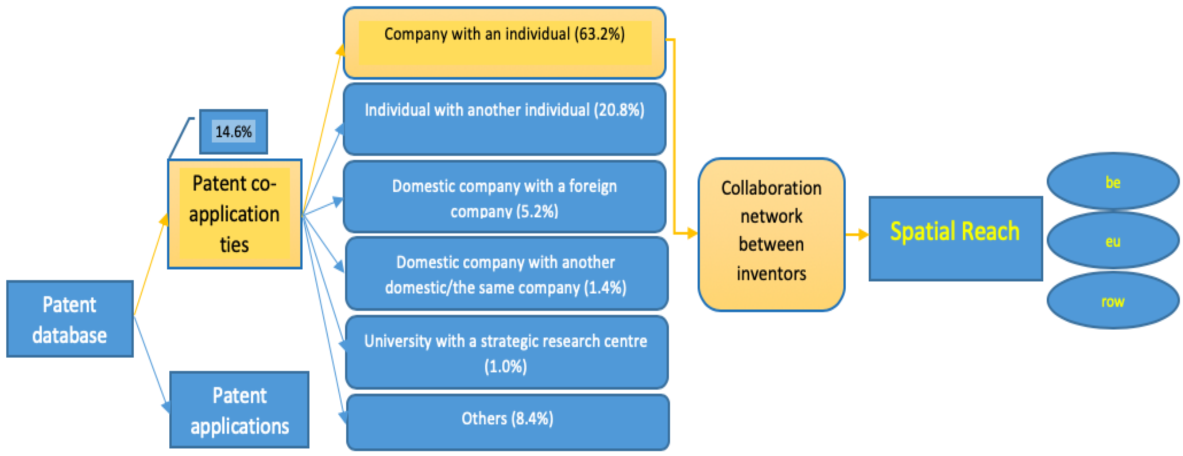
Sharing property rights on invention by companies, is a barely investigated topic (Hagedoorn 2003). However, we can observe the presence of a growth tendency in the number of co-applied patents during the last years. Some important aspects of joint patenting under the patent low have to be mentioned:

a. In the USA, each co-applicant (co-owner) of a patent is free to use his/her patent in particularly any way, without notifying the other applicants (owners) (see Title 35 USC § 262).
b. According to UK law each co-applicant (co-owner) does not have a right to use the patent without the consent of the other applicants (owners) (see 1977 Patents Act).

c. For European countries, the process is more complicated and ownership implications of joint patenting differ from country-to-country (Duguet 1994).

It is rather hard to understand and explain the economic and managerial rationales for joint patents behind this phenomenon. The study of Hagedoorn (2003) investigates the motivation of companies to enter into co-applied (co-ownership) agreements with the other companies. The author found out that companies with co-applied patents have higher possibilities to enter into co-owned patenting agreements. With respect to the company–individual joint patenting, we observe that individuals are inventors who either work in the company or do not have a link with the company. Although this distinction is not identifiable in the raw data, several manual samples indicated that these individuals are usually employees of the companies. According to Giuri and Mariani (2006), providing new information about the characteristics of European inventors, only one-third of the patents are developed by individual inventors, suggesting that most inventions are the outcome of a team activity while most of co-inventors belong to the same organisation. Based on the literature mentioned above the following question arises: What are the incentives and possible profit of the companies which apply for joint patents with individuals who are at the same time inventors belonging to the same company? One possible answer is that it boosts personal and social rewards of inventors, like personal satisfaction, prestige, reputation, and contribution of the inventors to the performance of the organisation and keep the inventors in the company.

**Figure IV-1. Structure of the patent database: types of patent co-application ties and spatial reach of patent collaboration networks**




Notes: own calculations, PATSTAT.

Further, the chapter focuses on patent collaboration network in company-individual patent co-application tie, where we consider inventors and not applicants; an approach that is also pursued in previous studies (Guellec and de la Potterie 2001; Giuri and Mariani 2006). Efforts are employed to identify the patent collaboration (see the descriptive statistics in Section 4). Using a similar approach as Bergek and Bruzelius (2010) a more detailed classification, based on identification of the collaboration, is developed: if a patent application is the result of a collaboration by multiple inventors residing in one or more countries, it is possible to identify a range of spatial levels on which patent collaboration occurs. This is called the 'spatial reach' of patent collaboration (see Figure IV-1). This approach includes (i) patent collaboration exclusively between domestic inventors from Belgium (BE); (ii) patent collaboration where at least one European inventor is involved (EU); (iii) patent collaboration where at least one inventor from the rest of the world (ROW) is engaged.

Table IV-1 shows the descriptive statistics on different types of collaboration among inventors in patent data. Table IV-1 presents the shares of patent collaboration according to the spatial reach for the period 2000-2013.

The research by Giuri and Mariani (2006) demonstrates that in six EU member states (Germany, Spain, France, Italy, Netherlands and United Kingdom) there are more than 20% of collaborative patents, with the Netherlands reaching 34.5%, and Germany 13.3% of patent collaborations. The highest share of patent collaboration, 31.4%, between companies and individuals occurs between domestic inventors in Belgium. Almost a quarter, 24.4%, of the patents have been the result of patent collaboration of companies with individuals from Belgium and from the rest of the world. We also found that some patent applications have no collaborations among inventors at all, in which case only one inventor is detected (17.1 %). The lowest shares in the spatial reach of patent collaboration by companies is observed with individuals from the rest of the world (9.1%), with individuals from the EU (5.2) and with individuals from the EU and individuals from the rest of the world (4.0%). Less than 1% of the original data contains missing information.

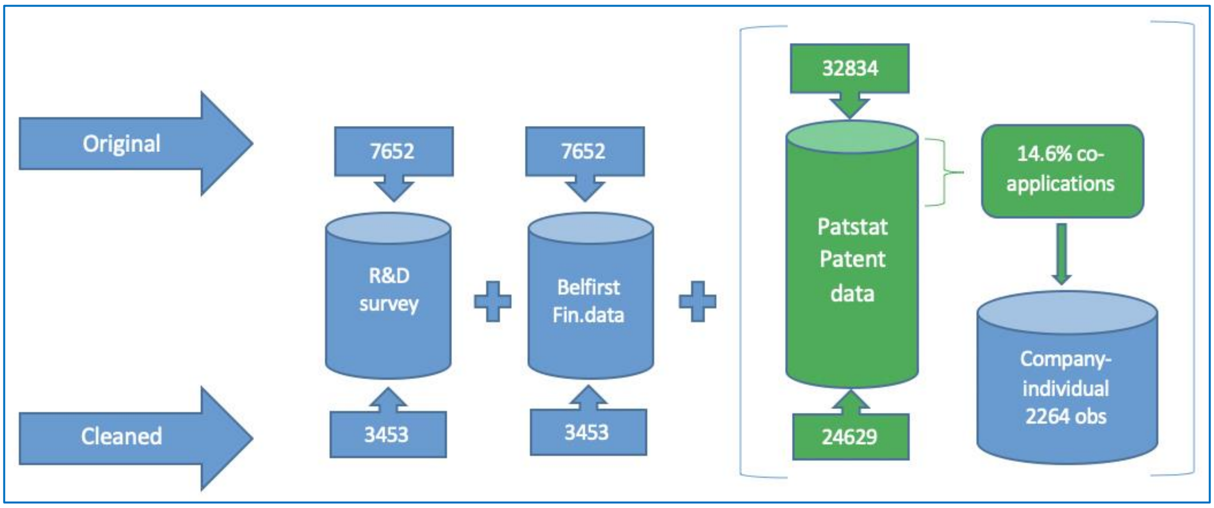
**Table IV-1. Statistics for the spatial reach of patent collaboration network between inventors (period 2000-2013)**

| Spatial reach of patent collaboration by companies with … | In % of total patent collaborations (N= 2,264) |
|---|---|
| … individuals from Belgium (be) | 64% |
| … individuals where at least one European inventor is involved (eu) | 16% |
| …individuals where at least one inventor from the rest of the world is engaged (row) | 21% |

Notes: own calculations

Next, all company names are verified in order to join the company –individual co-applied patent tie with the R&D and BELFIRST datasets because the patent data does not contain VAT numbers which usually serve as a unique identifier. In this way, the possibility of joining different data runs through the common names of the companies. In summary, the database consists of merging three different datasets. The process is illustrated in Figure IV-2.

**Figure IV-2. Development of the original database**




Source: author's own elaboration

Summarising, the dataset consists of an unbalanced panel of 7,652 companies in Belgium over the period 2000-2013. Correcting for missing values, the final sample has a more balanced panel of 3,453 R&D active companies. Next, the dataset is merged with patent data from PATSTAT on co-applied patents between companies and individuals yielding 2,264 observations, which contains information on patenting and detailed information about patent collaboration between inventors within company-individual co-application ties. This combination of datasets allows us to assess company-individual's joint patents with respect to the spatial reach of the patent collaboration network and the impact on output growth of R&D active companies in the three regions of Belgium.

## 4.3.2 Basic regression

Based on previous analyses on R&D productivity (Griliches 1987; Cincera 2005; Wieser 2005; Cincera et al. 2014), a general extended Cobb-Douglas production function is estimated (Hall et al. 2010).

$$Y_{it}=\lambda_t L_{it}^{\beta_1} C_{it}^{\beta_2} K_{it}^{\beta_3} e^{\varepsilon_{it}} \qquad (1)$$

where Y is output in terms of value added; L and C are labour and physical capital; K is the knowledge capital; $\beta_1$, $\beta_2$ and $\beta_3$ represent the elasticities of output with respect to each of the inputs; $\lambda_t$ is a set of time dummies; $e^{\varepsilon_{it}}$ is an error term, and the subscript i stands for company and t stands for time.

In order to estimate the following linear relationship, Eq. (1) is transformed to natural logarithms to estimate the elasticities $\beta_1$, $\beta_2$ and $\beta_3$:

$$y_{it} = \alpha + \lambda t + \beta_1 l_{it} + \beta_2 c_{it} + \beta_3 k_{it} + \varepsilon_{it} \qquad (2)$$

where lower case characters denote natural logarithms of variables. The R&D capital stock contributes to differences in productivity among companies and is measured using the Perpetual Inventory Method (Griliches 1979). This method assumes that the current stock of knowledge is the result of present and past R&D expenditure. The depreciation rate is assumed to be 15% and the pre-sample growth rate is set at 5% (Hall and Mairesse 1995). In the basic equation industry dummies are added to control for sector-specific and year dummies.

## 4.3.3 Patenting and patent collaboration as innovative activities of R&D active companies

The analysis of output growth is extended by implementing, first, the patent capability (Patenting) of the R&D active company. The second extension tests patent collaboration network (Collab) within a patent owned by the R&D active company. Patents are considered a meaningful measure of innovation. Collaborative networks are a crucial strategy for companies to access external knowledge and to improve their innovation performance (Powell et al. 1996). Two equations are estimated, expanding the baseline equation adding patents (Patenting) in equation 3 and collaboration (Collab) in equation 4 as independent variables.

$$y_{it} = \alpha + \lambda t + \beta_1 l_{it} + \beta_2 c_{it} + \beta_3 k_{it} + \gamma_1 Patenting_{it} + \varepsilon_{it} \qquad (3)$$

$$y_{it} = \alpha + \lambda t + \beta_1 l_{it} + \beta_2 c_{it} + \beta_3 k_{it} + \gamma_2 Collab_{it} + \varepsilon_{it} \qquad (4)$$

In equation 3 $Patenting_{it}$ refers to the patenting activity of company i. This independent variable takes the value of 1 if a company has at least one patent, and 0 otherwise. The $Collab_{it}$ variable expresses the presence of collaborative linkages among inventors within a company-individual joint patenting of the company i. More specific, $Collab_{it}$ takes the value of 1 if there is patent collaboration in producing a patent of company i, and 0 otherwise (see Appendix II-3, 3.1). Additionally, we include year, industry dummy variables and region dummies, to control for different productivity effects – value added, labour, physical capital and R&D stock – across the three regions in Belgium: the Brussels-Capital Region, the Flemish Region, and the Walloon Region.

### 4.3.4 The spatial reach of patent collaboration network involving company-individual ties

The research extends the examination of patent collaboration network, *Collab,* in a more detailed way by taking the spatial reach of the network into account. For that reason, the baseline equation includes variables on the spatial reach of the network.

$$y_{it} = \alpha + \lambda t + \beta_1 l_{it} + \beta_2 c_{it} + \beta_3 k_{it} + \gamma_3 be_{it} + \gamma_4 eu_{it} + \gamma_5 row_{it} + \varepsilon_{it} \qquad (5)$$

The variables covering the spatial reach of patent collaboration (e.g. BE, EU etc.) take the value of 1 if there is a spatial reach of patent collaboration in producing a patent of company i, and 0 otherwise. Additionally, we include year, industry dummy variables and region dummies, to control for different productivity effects – value added, labour, physical capital and R&D stock – across the three regions in Belgium. The descriptive statistics and variables' definitions are provided in Appendix II-3 (Table 3.1- 3.5).

## 4.4 Empirical analysis and results

### 4.4.1 The basic regression: Cobb-Douglass production function

The dependent variable in the analysis is presented by the output growth, in terms of value added, over the period 2000-2013. Ordinary least square (OLS) and quantile regressions are used to estimate the importance of various determinants of the company's output growth. Fixed and random effects models allow us to control for possible unobserved firms' fixed effects.

Table IV-2 reports the results from the estimation of the baseline equation. The dependent variable is the natural logarithm of value-added growth in the period 2000-2013 (y). The variable on R&D stock indicates towards a positive and significant influence on output in terms of value-added growth (y), with a rate of return to R&D stock of 4%. This means that one unit of R&D will lead to a growth in output of 0.04, or an R&D elasticity of 4 %. Similar results can be found in the work of Griffith et al. (2006) reported an R&D elasticity of 0.03. Verspagen (1995), using country data and industry dummies, estimates R&D elasticities of 0.05 to 0.17 (uncorrelated) and 0.06 to 0.17 (correlated), who find a rate of return about 5%. However, this value is lower than the average estimated rate. The determinants of our model are quite robust across the different model specifications. The output elasticities in the OLS regression for labour and capital are 86.8% and 13.8% respectively.

With respect to the regional differences, the Flemish Region reaches the highest rate of return to R&D stock (5.1%), whilst the Brussels-Capital Region shows similar R&D elasticities (4.7%) with the Walloon Region (4.7%). Capron and Meeusen (2000) test the distribution of the R&D productivity by regions in Belgium measured by the ratio of patents on R&D expenditure. The results demonstrate regional differences when companies are performing R&D activities. In our case the results vary slightly between regions which can be explained by a catch up rendering the technical gap between regions significantly smaller than ten years ago.

**Table IV-2. The impact of R&D stock on output growth by country and regional level**

| | OLS, robust | Random Effects | Fixed Effects | Quantile | *Regions in Belgium* Brussels-Capital Region (Quantile) | Flemish Region (Quantile) | Walloon Region (Quantile) |
|---|---|---|---|---|---|---|---|
| *Labour (l)* | 0.859*** | 0.884*** | 0.814*** | 0.857*** | 0.883*** | 0.830*** | 0.872*** |
| | (0.00427) | (0.00503) | (0.00692) | (0.00304) | (0.00680) | (0.00392) | (0.00678) |
| *Capital (c)* | 0.146*** | 0.087*** | 0.053*** | 0.133*** | 0.138*** | 0.142*** | 0.127*** |
| | (0.00285) | (0.00272) | (0.00314) | (0.00191) | (0.00408) | (0.00242) | (0.00450) |
| *R&D stock* | 0.043*** | 0.040*** | 0.022*** | 0.051*** | 0.047*** | 0.051*** | 0.047*** |
| | (0.00196) | (0.00328) | (0.00501) | (0.00169) | (0.00387) | (0.00217) | (0.00367) |
| *Year dummies* | yes | yes | yes | yes | yes | yes | yes |
| *Industry dummies* | yes | yes | no | yes | yes | yes | yes |
| *R-squared* | 0.914 | 0,930 | 0,902 | - | - | - | - |
| Pseudo $R_2$ | - | - | - | 0,742 | 0,787 | 0,731 | 0,753 |
| *F( $n_1$, $n_2$)* | 10723,7 | - | 1170,6 | - | - | - | - |
| *Prob > F* | 0,00 | 0,00 | 0,00 | - | - | - | - |
| *N(number of firm-year observations)* | 29536 | 29536 | 29536 | 29536 | 2819 | 19325 | 7392 |
| *Total N of firms ( all period)* | 3453 | 3453 | 3453 | 3453 | 364 | 2253 | 836 |
| *Hausman test* | In favour of Fixed Effects | | | | | | |

Notes: The OLS regression is adjusted to account for heteroscedasticity. Fixed and Random effects are used in order to control for heterogeneity in panel data.
* significance at 10% level; ** significance at 5% level; *** significance at 1% level.

Alternative estimation methods are used to examine the robustness of the results in Table IV-2. Quantile regression has distinct advantages (Baum 2013). While OLS can be inefficient if the errors are highly non-normal, quantile regression is more robust to non-normal errors and outliers. Quantile regression also provides a richer characterization of the data, allowing us to consider the impact of a covariate on the entire distribution of output growth, not merely its conditional mean. The coefficients obtained for the employment and the physical capital as well as for R&D stock are significant. The estimated elasticities for labour and capital are close to 0.7 and 0.3 respectively. In the case of R&D stock, the elasticity showed smaller than expected results due to sensitivity of results to missing values in our company survey data. In respect of the variation among different models, the outputs indicated a little variance (≈0.01) significance at the 1% level of significance. In addition, we controlled for industry differences in the OLS estimation. Some industry dummies showed high significance at the 1% level of significance (e.g. manufacturing, electronics, chemicals and others).

### 4.4.2 Influence of patenting on output growth by country and regional level

This section tests the influence of R&D active companies with company-individual co-application ties on output growth. Table IV-3 reports the results from the regressions examining whether there is any effect of patenting activity of company within the company-individual co-application ties on growth performance in terms of value added.

All previous results of Table IV-2 remain valid. The regression in Table IV-3 includes a dummy variable on patenting activity. This variable indicates whether the R&D active company has known a patent activity within the company-individual co-application ties during 2000-2013. Table IV-3 shows that the coefficient on patenting is positive and statistically significant, suggesting that co-applied patents of R&D active companies with individuals positively influences output growth. Such outcome is not surprising, since Scherer (1965), considering 365 of the largest US corporations, observes that inventions, measured by patents, have a positive effect on company profits via sales growth. Additionally, Bloom and Van Reenen (2002) state that patents have an economically and statistically significant impact on company-level productivity, where citation-weighted patent stock increases total factor productivity by 3%. Conversely, in the research of Coad and Rao (2008) companies with R&D and patenting activity perform poorly and experience negative sales growth.

**Table IV-3. The impact of patenting on output growth, country and regional level**

| | | | | | *Regions in Belgium* | | |
|---|---|---|---|---|---|---|---|
| | OLS, robust | Random Effects | Fixed Effects | Quantile | Brussels-Capital Region | Flemish Region | Walloon Region |
| | | | | | | Quantile | |
| *Labour (l)* | 0.859*** | 0.884*** | 0.814*** | 0.857*** | 0.883*** | 0.830*** | 0.872*** |
| | (0.00427) | (0.00503) | (0.00692) | (0.00319) | (0.00964) | (0.00390) | (0.00643) |
| *Capital (c)* | 0.145*** | 0.087*** | 0.053*** | 0.133*** | 0.138*** | 0.140*** | 0.127*** |
| | (0.00284) | (0.00272) | (0.00314) | (0.00201) | (0.00589) | (0.00241) | (0.00427) |
| *R&D stock* | 0.039*** | 0.040*** | 0.022*** | 0.049*** | 0.045*** | 0.047*** | 0.047*** |
| | (0.00200) | (0.00329) | (0.00501) | (0.00181) | (0.00553) | (0.00220) | (0.00354) |
| Patenting | 0.107*** | 0.052*** | 0.018 | 0.094*** | 0.034 | 0.140*** | -0.003 |
| | (0.0125) | (0.0142) | (0.0154) | (0.0115) | (0.0437) | (0.0133) | (0.0235) |
| *Year dummies* | yes | yes | yes | yes | yes | yes | yes |
| *Industry dummies* | yes | yes | no | yes | yes | yes | yes |
| *R-squared* | 0.914 | 0.930 | 0.903 | - | - | - | - |
| *Pseudo* $R_2$ | - | - | - | 0.742 | 0.787 | 0.732 | 0.753 |
| *F(* $n_1$*,* $n_2$*)* | 10357.3 | - | 987.9 | - | - | - | - |
| *Prob > F* | 0.00 | 0.00 | 0.00 | - | - | - | - |
| *N(number of firm-year observations)* | 29536 | 29536 | 29536 | 29536 | 2819 | 19325 | 7392 |
| *Hausman test* | *In favour of Fixed Effects* | | | | | | |

Notes: * significance at 10% level; ** significance at 5% level; *** significance at 1% level.

Several diagnostic methods seek to identify potential problems. All models show results that are highly statistically significant. The quantile regression shows the highest values in all coefficients. Table IV-3, again, finds substantially different effects of patenting activity on output growth in one region. The Flemish Region indicate a positive and significant effect of patenting activity on companies' output growth. Capron and Meeusen (2000) attribute this to the technical performance of the regions in Belgium. Based on their results, the Flemish Region is characterized by the highest effects of R&D stock and patent activity. The Brussels-Capital Region output is not statistically significant, which can be explained by the fact that researchers who work in Brussels, live in the Flemish Region or in the Walloon Region. The Walloon Region shows the weakest performance because of the insignificance of its coefficient with respect to patent activity. This might be due to the industrial specialisation pattern as well as the research orientation of companies.

### 4.4.3 The impact of patent collaboration networks on output growth at country and regional level

This section investigates the impact of patenting R&D active companies with patent collaboration networks among inventors, involved in companies and individuals co-application relations, on output growth.

**Table IV-4. The impact on output growth of patent collaborations networks involving company and individual co-application ties**

| | | | | | *Regions in Belgium* | | |
|---|---|---|---|---|---|---|---|
| | OLS, robust | Random Effects | Fixed Effects | Quantile | Brussels-Capital Region | Flemish Region | Walloon Region |
| | | | | | Quantile | | |
| *Labour (l)* | 0.859*** | 0.872*** | 0.858*** | 0.851*** | 0.885*** | 0.830*** | 0.872*** |
| | (0.00427) | (0.00829) | (0.00827) | (0.00314) | (0.00986) | (0.00394) | (0.00643) |
| *Capital (c)* | 0.145*** | 0.153*** | 0.151*** | 0.135*** | 0.137*** | 0.141*** | 0.128*** |
| | (0.00283) | (0.00541) | (0.00537) | (0.00196) | (0.00597) | (0.00244) | (0.00427) |
| *R&D stock* | 0.040*** | 0.039*** | 0.046*** | 0.049*** | 0.044*** | 0.048*** | 0.048*** |
| | (0.00199) | (0.00503) | (0.00496) | (0.00177) | (0.00563) | (0.00222) | (0.00354) |
| *Collab* | 0.121*** | 0.102*** | 0.084** | 0.097*** | 0.196*** | 0.129*** | -0.026 |
| | (0.0153) | (0.0377) | (0.0384) | (0.0130) | (0.0508) | (0.0158) | (0.0284) |
| *Year dummies* | yes | yes | yes | yes | yes | yes | yes |
| *Industry dummies* | yes | yes | no | yes | yes | yes | yes |
| *R-squared* | 0.914 | 0.930 | 0.932 | - | - | - | - |
| *Pseudo* $R_2$ | - | - | - | 0.742 | 0.787 | 0.732 | 0.753 |
| $F(n_1, n_2)$ | 10451.2 | - | 1115.7 | - | - | - | - |
| *Prob > F* | 0.00 | 0.00 | 0.00 | - | - | - | - |
| *N(number of firm-year observations)* | 29536 | 29536 | 29536 | 29536 | 2819 | 19325 | 7392 |
| *Hausman test* | *In favour of Fixed Effects* | | | | | | |

Notes: * significance at 10% level; ** significance at 5% level; *** significance at 1% level.
We have analysed the dataset which included only companies which do not collaborate. The results reveal no impact on performance of the companies.

Table IV-4 looks at the behaviour of R&D active companies with regard to collaborative networks between inventors in company-individual co-application relations. Collaboration is an inherent aspect of the research activity, because the information exchange reinforces the discussion and the production of new knowledge (Katz and Martin 1997; Heinze and Kuhlmann 2008; Ortega 2011). Patent collaborations are one channel of knowledge diffusion from one country to another. The results in Table IV-4 suggest that knowledge flows through patent collaborations networks involving an R&D active company and individuals are meaningful, and the coefficient indicates a positive and significant effect on the company's output growth. Table IV-4 shows that patent collaboration networks at the regional level have a positive and significant effect, pointing to the existence of regional differences. However, the coefficient of the Walloon Region is not statistically significant, which might be due to the historical economic development of this region and its outdated industrial base (Capron and Meeusen 2000).

### 4.4.4 The impact of the spatial reach of the patent collaboration networks on output growth

Table IV-5 explores the impact of the spatial reach of the patent collaboration network involving company-individual ties on output growth. Table IV-5 provides information on the most successful type of spatial reach (national, European and/or international) of patent collaboration network in its impact on the company's output growth.

As in previous tables, the dependent variable is output growth in terms of value added (and measured in natural logarithms). The results in Table IV-5 introduce a second spatial dimension in terms of the spatial reach of patent collaboration: Belgium, EU and rest of the world. At the Belgian level the OLS regression points to a significant impact on output growth when the patent involves a collaboration with patent inventors located in Belgium, or involving a broader spatial reach where at least one inventor from Europe and the rest of the world engaged in collaboration.

Table IV-5 confirms that the spatial reach of patent collaboration networks contributes to the company's output growth. Collaborations between inventors where at least one inventor is coming from the rest of the world (ROW) are the most contributing networks, followed by patent collaboration networks involving at least one inventor from the EU (EU). Patent collaboration between only Belgian inventors do not indicate any importance. These results confirm the findings of Guellec and van Pottelsberghe de la Potterie (2000), who assess, using granted EPO patents, the extent to which some attributes of a patent are related to its value. They posit that "International co-operation seems even more fruitful than domestic co-operation" (Guellec and van Pottelsberghe de la Potterie 2000, p.112). Similar results are found by Cincera et al. (2003) who focus on the role of knowledge in explaining the performance at the company level, by augmenting the classic productivity growth approach with R&D cooperation. Their findings confirm the positive effect of foreign cooperation on sales growth and indicate a significantly negative influence on sales growth by interaction term with national R&D cooperation (Cincera et al. 2003). Similarly, Archibugi and Pianta (1996) conclude that international patent collaborations are revealed in the rapid growth of patents with inventors from different countries.

**Table IV-5. The spatial reach of the patent collaboration networks on output growth**

| | *Belgium* | | *Regions in Belgium* | | |
|---|---|---|---|---|---|
| | OLS, robust | Quantile | Brussels-Capital Region | Flemish Region | Walloon Region |
| | | | | Quantile | |
| *Labour (l)* | 0.858*** | 0.856*** | 0.885*** | 0.827*** | 0.874*** |
| | (0.00427) | (0.00316) | (0.00964) | (0.00385) | (0.00641) |
| *Capital (c)* | 0.146*** | 0.133*** | 0.136*** | 0.141*** | 0.127*** |
| | (0.00282) | (0.00198) | (0.00581) | (0.00238) | (0.00426) |
| *R&D stock* | 0.039*** | 0.047*** | 0.043*** | 0.047*** | 0.046*** |
| | (0.00199) | (0.00179) | (0.00552) | (0.00217) | (0.00352) |
| *be* | 0.034** | 0.012 | 0.117* | 0.027 | -0.046 |
| | (0.0166) | (0.0161) | (0.0628) | (0.0188) | (0.0322) |
| *eu* | 0.070* | 0.145*** | 0.303** | 0.215*** | -0.191*** |
| | (0.0392) | (0.0319) | (0.154) | (0.0357) | (0.0678) |
| *row* | 0.462*** | 0.452*** | 0.460*** | 0.442*** | 0.478*** |
| | (0.0335) | (0.0288) | (0.0920) | (0.0317) | (0.0873) |
| *Year dummies* | yes | yes | yes | yes | yes |
| *Industry dummies* | yes | yes | yes | yes | yes |
| *R-squared* | 0.915 | - | - | - | - |
| *Pseudo $R_2$* | - | 0.744 | 0.739 | 0.762 | 0.753 |
| *F( $n_1$, $n_2$)* | 9059.44 | - | - | - | - |
| *Prob > F* | 0.00 | - | - | - | - |
| *N(number of firm-year observations)* | 29536 | 29536 | 2819 | 19325 | 7392 |

Notes: * significance at 10% level; ** significance at the 5% level; *** significance at 1% level.
See Random and Fixed Effects models in Appendix II-5

The empirical results raise the question why patent collaboration with foreign inventors have a stronger influence on the output growth of the R&D active companies than neighbouring EU countries. A possible explanation is that patent activities depend on a few companies which account for more than 20% of all Belgian applications (Capron et al. 1998). These companies are often subsidiaries of foreign multinationals. Guellec and van Pottelsberghe de la Potterie (2000) state that the collaboration with foreign countries is increasing if a country's share of domestic inventions controlled by foreign companies is high. Above findings imply that, overall, technical innovations involving inventors in the rest of the world complements the knowledge in Belgium and leads to a positive impact on output growth.

The OLS (robust) regression corroborates the previous findings, but also finds a significant impact on patent inventors collaborating within Belgium.

The three columns at the right-hand side of Table IV-5 show the results on the spatial reach for the three regions in Belgium. If an inventor from Belgium is involved, the growth of value added in the Flemish Region benefits most from patent collaboration where at least one inventor from the rest of the world is engaged. Also, the patent collaboration involving the combination of inventors with at least one inventor originated from the EU have a significant positive effect in the growth of value added. However, in this case, the effects prove stronger in the other regions in Belgium. Growth of value added in the other regions in Belgium benefit significantly more from patent collaboration when a combination of inventors with at least one inventor from the rest of the world is included.

A strong negative significance for the Walloon Region also emerges from patent collaboration in the case of an exclusive involvement of inventors from the EU.

In summary, a spatial reach with involvement of inventors from the rest of the world and the EU benefits output growth in the Flemish Region and the Walloon region; whereas a spatial reach with involvement only Belgian inventors exclusively benefits output growth in the Brussels-Capital Region.

Additionally, few empirical tests have been conducted with elaborated classification on spatial reach. A more detailed classification, based on identification of the collaboration, is proposed. This approach includes (i) patent collaboration exclusively between domestic inventors from Belgium (BE); (ii) patent collaboration between domestic and European inventors (BE-EU); (iii) patent collaboration between domestic inventors and those located in the rest of the world (BE-ROW); (iv) patent collaboration between domestic inventors and those from the EU and from countries in the rest of the world (BE-EU-ROW); (v) patent collaboration exclusively between European inventors (EU); (vi) patent collaboration between inventors from the EU and from countries in the rest of the world (EU-ROW); and (vii) patent collaboration exclusively between inventors in the rest of the world (ROW). However, some issues with data on elaborated classification of spatial reach are detected during its processing. For some types of spatial reach (BE-EU-ROW, EU-ROW), the number of observations is less than 50 cases which imply additional empirical constrains (see Appendix II-3**,** Table 3.5). Hence, the empirical results with inclusion of elaborated spatial reach showed similar trends as in Table IV-5.

## 4.5 Robustness check

We conduct additional tests designed primarily to ensure the robustness of the sign and significance pattern of the empirical model reported in Table IV-2 and summarized these in Table IV-6 and Table IV-7.

Table IV-6 shows additional results of the R&D production function to assess the robustness of the elasticity of the firm's R&D stock with respect to output. Table IV-2 showed a primary result of R&D elasticity of 4.1%. This result is about the same when we use new constructed R&D stock (column 1 of Table IV-6). New construction of R&D stock includes the same perpetual inventory method, but with additional cleaning, where we remove breaking consequent line observations. A second possibility is that the results may reflect differences due to the construction of physical capital. Considering a direct measure of physical capital in place of the constructed physical capital using a perpetual inventory method (column 2) also leads to similar results for the R&D stock elasticity. The estimated R&D stock elasticity is slightly lower when the turnover is used to measure the firm's output (with new (column 3) and old (column 4) ways to construct R&D stock).

**Table IV-6. Robustness of the R&D stock elasticity**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Labour (l)* | 0.811*** | 0.806*** | 0.759*** | 0.760*** |
| | (0.00530) | (0.00557) | (0.00699) | (0.00698) |
| *Capital (c)* | 0.157*** | 0.173*** | 0.201*** | 0.201*** |
| | (0.00334) | (0.00383) | (0.00427) | (0.00430) |
| *R&D stock* | 0.051*** | 0.042*** | 0.025*** | 0.020*** |
| | (0.00229) | (0.00217) | (0.00331) | (0.00314) |
| *Year dummies* | yes | yes | yes | yes |
| *Industry dummies* | yes | yes | yes | yes |
| *R-squared* | 0.899 | 0.898 | 0.811 | 0.811 |
| $F(n_1, n_2)$ | 5850.16 | 5736.5 | 3044.7 | 3029.1 |
| *Prob > F* | 0.00 | 0.00 | 0.00 | 0.00 |
| *N(number of firm-year observations)* | 20967 | 20967 | 20967 | 20967 |

Notes: * significance at 10% level; ** significance at the 5% level; *** significance at 1% level.

(1) new constructed R&D stock
(2) constructed physical capital using a PIM
(3) turnover with new construct R&D stock
(4) turnover with old construct R&D stock

Finally, besides traditional panel data methods, i.e. between, fixed and random effects models which allow one to control for possible unobserved firms' unobserved fixed effects, we also estimated Two-Step SYSGMM (Table IV-7). These models also allow one to consider the possible endogeneity or simultaneity issue of the explanatory variables with the error term.
The validity of the set of instruments can be tested through the Sargan or Hansen over-identification tests. The null hypothesis is that the instruments are valid, i.e. they are uncorrelated with the error terms. Under the null hypothesis, the test statistic follows a chi-squared distribution with a number of degrees of freedom being equal to the number of over-identifying restrictions. Rejection of the null hypothesis casts a doubt on the validity of the set of instruments.[28] This suggests that both tests are invalid. This may explain why we observe a somewhat lower elasticity for the physical capital, while for the estimated R&D elasticity a similar finding is observed compared to the benchmark. The initial-conditions assumption for Two-Step SYSGMM model is the following: the instruments $y_{i,t-2}$, $y_{i,t-3}$, . . . are weakly correlated with the first-differenced lagged dependent variable $\Delta y_{i,t-1}$ when $\lambda \to 1$. Additional

[28] One possible explanation of such outcome is due to sensitivity of results to missing values in our company survey data.

moment conditions for the level model are presented: lagged dependent variable, strictly exogenous or predetermined regressors and endogenous regressors. Further lags for the level model are redundant.

**Table IV-7. Robustness of the R&D stock elasticity using Two-Step SYSGMM method**

| | Two-Step SYSGMM |
|---|---|
| *L.Value added* | 0.187*** (0.0221) |
| *Labour (l)* | 0.765*** (0.0349) |
| *Capital (c)* | 0.043*** (0.00981) |
| *R&D stock* | 0.047*** (0.0146) |
| *year* | 0.016*** (0.00111) |
| *Sargan* | 0.000 |
| *Hansen* | 0.000 |
| *AR(1)* | 0.000 |
| *AR(2)* | 0.188 |
| *N(number of firm-year observations)* | 26168 |

Notes: * significance at 10% level; ** significance at the 5% level; *** significance at 1% level.

## 4.6 Conclusions

This chapter examined the performance in terms of output growth of research active companies with spatially diversified patent collaboration networks. The research responded to the following gaps in the literature: (i) analysis of different patterns of patent collaboration networks involving companies and individuals, thus adding to the debate on boundary spanning in regional innovation systems; and (ii) use of original data on patent collaborations in research active companies with attention to knowledge distribution between companies and individuals; and (iii) implementation of a novel approach by including the spatial reach of patent collaboration networks. The main contribution of this chapter is not merely to replicate measurement of the returns to R&D, but to supplement it by including the spatial reach of patent collaboration networks and its impact on firms' output growth.

Several facts about co-applied patents are found. 14.6 % of all patent applications are the result of co-application relations which is indicating a growth trend in the number of co-applied patents in recent decades. Additionally, we distinguish about 50 different types of patent co-application ties between different organisations. The highest share of co-applied patents involves mainly between companies and individuals (63.2%), over 20% of individuals co-apply with other individuals, and 5.2% domestic companies co-apply with foreign companies on patents. Hence, the main focus in this chapter rests on company-individual co-application relationships.

Based on the Cobb-Douglas production function and panel data, the chapter aims at assessing the measurement of the returns to R&D, based on the spatial reach of patent collaboration networks and its impact on output growth. Results from the estimation of the baseline equation show a positive and significant impact of R&D stock on output growth, with a rate of return 4%. These results are in line with the literature. Further investigations in terms of regional differences indicate slight variations of R&D rate of returns between regions which can be explained by a catching up process associated with a smaller technical gap between regions compared to ten years ago.

Based on the analysis of the impact of patenting activities of R&D companies within the company-individual co-application ties on output growth, the results suggest that co-applied patents of the firms positively influence output growth. Additionally, we observed substantial different effects of patenting activity on output growth only in one region, where the Flemish Region is characterized by a positive and significant effect of patenting activity on companies' output growth and the Walloon Region and the Brussels-Capital exhibit a weaker performance. Such trends can be explained by the industrial specialisation pattern, technical performance of the regions as well as the research orientation of companies in the regions.

The chapter also investigated the behaviour of R&D active companies regarding patent collaboration networks between inventors in company-individual co-application tie. Results suggest that knowledge flows through patent collaborations networks, involving an R&D active company and individuals, yield a positive and significant effect on the company's output growth. Further analysis also highlighted the existence of regional differences.

Finally, we investigated the impact of the spatial reach of the patent collaboration networks involving company-individual ties on output growth. We observed significant impact on output growth when the patent involves a collaboration with at least one patent inventor located in the rest of the world or involving a spatial reach where at least one inventor from the. The collaborations among individuals with at least one inventor from the rest of the world (ROW) is the network contributing the most, followed by patent collaboration networks involving at least one individual from the EU (EU). Technical innovations involving inventors in the rest of the world complements the knowledge in Belgium and leads to a positive impact on output growth. Regarding the regional differences, a spatial reach with involvement of inventors from the rest of the world and the EU benefits output growth in the Flemish Region and the Walloon region, whereas a spatial reach with involvement only Belgian inventors exclusively benefits output growth in the Brussels-Capital Region.

For the period 2000-2013, the results demonstrate a positive and significant impact on the company's output growth when R&D active companies are involved in a patent activity with individuals. However, the most influential R&D companies with company-individual co-application relations in terms of output growth are those ones which involve international collaboration networks. These findings suggest that further motivation and implication of R&D companies to enter into co-applied agreements with foreign inventors (individuals) may positively increase the output growth of a firm. As emphasized by Kumar and Margun (1998), joint innovation activities have a tendency to lower the costs for developing new technologies, as well as eliminating the effort of producing duplicated research, allow collaborators to share the risk related to R&D and help to get a faster access to other necessary sources in order to finalize such complex projects. Due to the country size, Belgium is not able to have sufficient resources to cover all range of technological fields in comparison with large countries. Hence, the expansion of bi-lateral science and technology agreements with other countries can positively influence and as well encourage R&D companies to be engaged into co-application patenting processes. However, intra-regional collaborations are more important than inter-regional ones due to the evidence of a spreading-out process of regional innovation systems (Capron and Cincera 1999). The results obtained for the Belgian regions in our chapter indicate a marked contrast between regions. The policy focus should be put to stimulate the diffusion of knowledge, S&T policy at regional level, in order to improve intra-regional collaborations. The emphasis of collaboration networks in turn will increase regional competitiveness.

## Appendix II

### Appendix II-1 Representativeness of the R&D database

**Table 1.1 Representativeness of the R&D database: R&D expenditure from applied dataset in % of the main science and technology indicator BERD**

| year | R&D expenditure from balanced panel dataset | R&D expenditure from used in regression dataset | BERD from OECD | % (a) | % (b) |
|---|---|---|---|---|---|
| | million euro | million euro | million euro | | |
| 2000 | 2479,7 | 2387,5 | 3588,6 | 69,1 | 66,5 |
| 2001 | 2766,5 | 2629,8 | 3921,1 | 70,6 | 67,1 |
| 2002 | 2804,3 | 2716,6 | 3662,4 | 76,6 | 74,2 |
| 2003 | 2771,5 | 2685,5 | 3607,9 | 76,8 | 74,4 |
| 2004 | 3056,5 | 2923,9 | 3731,8 | 81,9 | 78,4 |
| 2005 | 3073,4 | 2934,0 | 3775,6 | 81,4 | 77,7 |
| 2006 | 3559,8 | 3320,2 | 4105,6 | 86,7 | 80,9 |
| 2007 | 3691 | 3510,8 | 4420,4 | 83,5 | 79,4 |
| 2008 | 4023,4 | 3802,3 | 4650 | 86,5 | 81,8 |
| 2009 | 3984,4 | 3791,2 | 4574,8 | 87,1 | 82,9 |
| 2010 | 4102,3 | 3897,6 | 5027,7 | 81,6 | 77,5 |
| 2011 | 4597,8 | 4394,4 | 5613,4 | 81,9 | 78,3 |
| 2012 | 5173,1 | 4984,0 | 6149 | 84,1 | 81,1 |
| 2013 | 5363,5 | 5167,4 | 6356,8 | 84,4 | 81,3 |
| N of firms for all period | 3686 | 3453 | | 3686 | 3453 |

In order to estimate that our R&D dataset do not have any systematic difference except for the treatment applied, we produce a comparison of the initial data on R&D expenditure (with cleaned and adopted version to our research) with the main science and technology indicator BERD. According to the Table 1.1, where R&D expenditure compared with the main science and technology indicator BERD, we obtained R&D expenditures above 40%. Such results indicate substantial level of the representativeness of our modified dataset.

### Appendix II-2 Co-applied patent networks between different organisations

All variables listed below are presented as a dummy variable (1 if the patent application has a co-application, 0 otherwise). Table 2.1 shows the shares of each type of co-applied patent networks between different organisations with at least one assignee from Belgium.

**Table 2.1 Co-applied patent networks between different organisations with at least one assignee from Belgium**

| Cooperation | % | Cooperation | % |
|---|---|---|---|
| company_individual | 63.15 | StrategicResearchCentre_university_ universityForeign | 0.084 |
| Individual_individual | 20.81 | university_company_universityForeign | 0.084 |
| company_companyForeign | 5.19 | government_universityForeign_nonprofit_university | 0.084 |
| company_company | 1.42 | CollectiveResearchCentre_individual | 0.056 |
| university_ StrategicResearchCentre | 1.03 | company_CollectiveResearchCentre | 0.056 |
| university_individual | 1 | university_CollectiveResearchCentre | 0.056 |
| company_StrategicResearchCentre | 0.78 | university_government | 0.056 |
| university_university | 0.67 | company_CollectiveResearchCentre_individual | 0.056 |
| university_company | 0.59 | government_government | 0.056 |
| company_ government | 0.53 | nonprofit_StrategicResearchCenter | 0.056 |
| company_universityForeign | 0.5 | university_StrategicResearchCentre_ _StrategicResearchCentreForeign | 0.056 |
| individual_StrategicResearchCentre | 0.42 | individual_CollectiveResearchCentre_university | 0.028 |
| company_StrategicResearchCentre_ _university | 0.42 | individual_nonprofit_university | 0.028 |
| company_individual_ universityForeign | 0.42 | company_universityForeign_government_nonprofit | 0.028 |
| individual_ universityForeign | 0.28 | government_StrategicResearchCentre | 0.028 |
| company_university_individual | 0.28 | company_hospital_individual | 0.028 |
| individual_company_ _StrategicResearchCentre | 0.25 | government_university_universityForeign | 0.028 |
| government_ individual | 0.2 | university_StrategicResearchCentre_nonprofit | 0.028 |
| individual_nonprofit | 0.17 | universityForeign_StrategicResearchCentre | 0.028 |
| government_universityForeign | 0.17 | company_government_StrategicResearchCentre_ _university | 0.028 |
| individ_StrategicResearchCentre_ _university | 0.17 | nonprofit_universityForeign | 0.028 |
| company_government_universityForeign | 0.14 | nonprofit_nonprofit | 0.028 |
| company_nonprofit | 0.11 | government_nonprofit | 0.028 |
| university_universityForeign | 0.11 | company_individual_universityForeign_nonprof | 0.028 |
| individual_company_government | 0.11 | company_government_nonprofit | 0.028 |

Notes:company_individual– co-application of a company with an individual
individual_individual – co-application of an individual with another individual
company_companyForeign - co-application of a Belgian company with a foreign company
company_company – co-application of a Belgian company with another Belgian company or the same company
university_StrategicResearchCentre – co-application of an university with a strategic research centre
university_individual – co-application of an university with an individual
company_StrategicResearchCentre - co-application of a company with strategic research centre
university_university – co-application of an university with another university
university_company – co-application of an university with a company
company_government– co-application of a company with government
company_universityForeign – co-application of a company with a foreign university

**Appendix II-3 Variable definition and descriptive statistics**

**3.1 Survey variables**

*y:* logarithm of the output growth, measured in terms of value added, between 2000-2013

*l:* logarithm of the labour growth between 2000-2013

*c:* logarithm of the capital growth between 2000-2013

*r&d stock:* logarithm of the R&D capital stocks between 2000-2013, constructed using the Perpetual Inventory Method (PIM)

*Patenting:* Dummy variable that equals 1 if the company has a co-applied patent and 0 otherwise

*Collab:* Dummy variable that equals 1 if there is patent collaboration among inventors within a company-individual joint patenting in producing a patent of company i, and 0 otherwise

Table 3.1 provides information about the constructed variables for the spatial reach divided into seven categories.

**Table 3.1 Variables constructed**

| Variable | Description | Explanation |
|---|---|---|
| be | Only collaboration within Belgian inventors | Take the value of 1 if there is a spatial reach of patent collaboration in producing a patent of company i, and 0 otherwise |
| eu | Collaboration between inventors where at least one inventor for the EU | |
| row | Collaboration between inventors where at least one inventor for the rest of the world | |

**Table 3.2 Descriptive statistics**

| | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| *y* | 29536 | 8.184 | 1.715 | .355 | 14.969 |
| *l* | 29536 | 3.795 | 1.548 | .693 | 9.788 |
| *c* | 29536 | 7.636 | 2.367 | .027 | 17.718 |
| *r&dstock* | 29536 | 7.194 | 1.981 | .511 | 15.836 |
| *Collab* | 29536 | .052 | .222 | 0 | 1 |
| *Patenting* | 29536 | .075 | .263 | 0 | 1 |

**Table 3.3 Correlation matrix**

| | *y* | *l* | *c* | *r&dstock* | *Collab* | *Patenting* |
|---|---|---|---|---|---|---|
| *y* | 1 | | | | | |
| *l* | 0.945*** | 1 | | | | |
| *c* | 0.817*** | 0.779*** | 1 | | | |
| *r&dstock* | 0.532*** | 0.512*** | 0.441*** | 1 | | |
| *Collab* | 0.221*** | 0.198*** | 0.215*** | 0.276*** | 1 | |
| *Patenting* | 0.198*** | 0.175*** | 0.1089*** | 0.255*** | 0.824*** | 1 |

Notes: * significance at 10% level; ** significance at the 5% level; *** significance at 1% level.

**Table 3.4 The spatial reach of the patent collaboration network profile among R&D active companies within company-individual co-application type**

| | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| *be* | 29536 | .034 | .181 | 0 | 1 |
| *eu* | 29536 | .008 | .091 | 0 | 1 |
| *row* | 29536 | .011 | .101 | 0 | 1 |

Notes: own calculations

**Table 3.5 The distribution of the spatial reach of the patent collaboration network among R&D active companies within company-individual co-application type (elaborated version)**

| The spatial reach of the patent collaboration networks | % |
|---|---|
| *be* | 66 |
| *be_row* | 9 |
| *be_eu* | 9 |
| *eu_row_be* | 2 |
| *row* | 9 |
| *eu* | 3 |
| *eu_row* | 2 |

Notes: own calculations

After joining R&D data and financial data (Belfirst) with patent data (PATSTAT, only patent applications with company-individual co-application type), we identified R&D active companies which hold co-applied patents for the period 2000-2013. In this chapter we decompose the spatial reach into seven categories. Table 3.5 presents the shares of the spatial reach of the patent collaboration network among R&D active companies. The most common collaboration relations in patenting among R&D active companies are among Belgian inventors and between Belgian inventors in collaboration with inventors from the rest of the world countries. Patent collaboration networks involving individuals from Belgium and the rest of the world (EU-ROW) represent only 9%. All other categories of the spatial reach are below 10%.

**Appendix II-4 Tests**

**4.1 Omitted-variable test**

Ramsey RESET test using powers of the fitted values of *y* - logarithm of the output growth
Ho: model has no omitted variables
$F(3, 29495) = 4.47$
Prob > F =0.0038

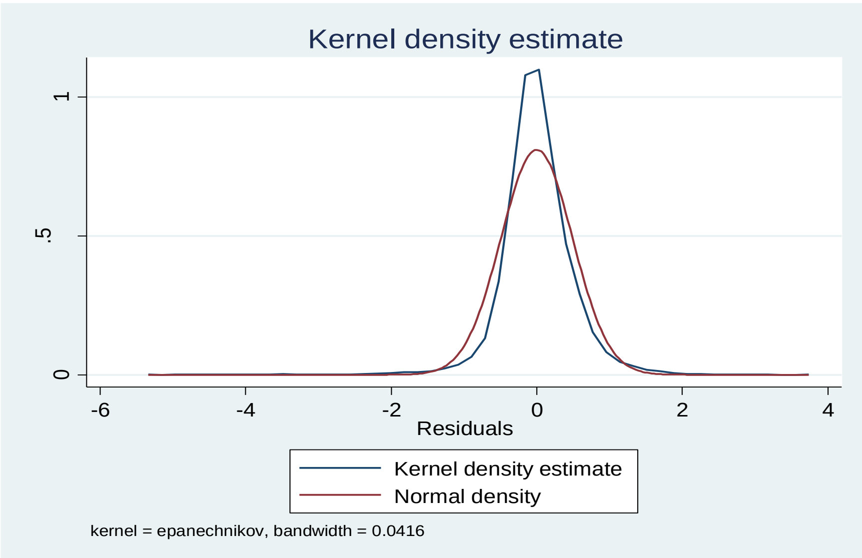
The results of the Ramsey RESET test for omitted variables illustrate no evidence of omitted-variables bias, the p-value is higher than the usual threshold of 0.05 (95% significance), so we fail to reject the null and conclude that we do not need more variables.

**Table 4.1 Multicollinearity**

| Variable | VIF | 1/VIF | VIF | 1/VIF | VIF | 1/VIF | VIF | 1/VIF |
|---|---|---|---|---|---|---|---|---|
| *l* | 3.05 | 0.328 | 2.93 | 0.341 | 2.93 | 0.341 | 2.94 | 0.341 |
| *c* | 2.86 | 0.349 | 2.71 | 0.369 | 2.71 | 0.369 | 2.71 | 0.369 |
| *r&dstock* | 1.58 | 0.632 | 1.55 | 0.644 | 1.54 | 0.648 | 1.54 | 0.648 |
| patenting | | | 1.10 | 0.906 | | | | |
| collab | | | | | 1.08 | 0.922 | | |
| be | | | | | | | 1.05 | 0.954 |
| eu | | | | | | | 1.04 | 0.959 |
| row | | | | | | | 1.05 | 0.953 |

The multicollinearity diagnostic performed in the Table 4.1, using a correlation matrix and variance inflation factor (VIF), shows that our independent variables are not correlated with each other, leading to precise estimation. However, due to heteroscedasticity issue, robust standard error was used.

**Figure 4.1 Testing for normality**




Another assumption of the regression model (OLS) that impact the validity of all tests (p, t and F) is that residuals behave "normal". Here residuals seem to follow a normal distribution.

## Appendix II-5 The spatial reach of the patent collaboration networks on output growth

**Table 5.1 The spatial reach of the patent collaboration networks on output growth (Random and Fixed effects models)**

| | *Belgium* | |
|---|---|---|
| | Random Effects | Fixed Effects |
| *Labour (l)* | 0.883*** | 0.814*** |
| | (0.00502) | (0.00692) |
| *Capital (c)* | 0.086*** | 0.053*** |
| | (0.00272) | (0.00314) |
| *R&D stock* | 0.038*** | 0.022*** |
| | (0.00331) | (0.00501) |
| *be* | 0.153*** | -0.068 |
| | (0.0387) | (0.0973) |
| *eu* | 0.004 | -0.222*** |
| | (0.0519) | (0.0787) |
| *row* | 0.353*** | 0.055 |
| | (0.0542) | (0.0999) |
| *Year dummies* | yes | yes |
| *Industry dummies* | yes | yes |
| *R-squared* | 0.930 | 0.902 |
| $F(n_1, n_2)$ | - | 847.9 |
| *Prob > F* | 0.00 | 0.00 |
| *N(number of firm-year observations)* | 29536 | 29536 |

Notes: * significance at 10% level; ** significance at the 5% level; *** significance at 1% level.

In order to decide between fixed or random effects, we run a Hausman test, to check whether the unique errors are correlated with the regressors. The Hausman test indicated the positive results in favour of fixed effects model.

## CHAPTER V

# THE NETWORK CHARACTERISTICS OF INNOVATORS AND THEIR PRODUCTIVITY PERFORMANCE: VARIETY AND SPATIAL REACH

This chapter is based on the INNOVIRIS project "Prospective research for Brussels 2014", "Brussels knowledge flows: localised learning and regional knowledge pipelines (BLOCPIPE)", ULB, Belgium.

**SUMMARY**

*Inter-organisational relations are a crucial aspect of knowledge flows, which are at the same time an important engine for innovation. Collaboration has become an ever more important feature of entrepreneurial strategy to innovate. Network ties facilitate companies' innovative capabilities by acting as key sources for innovations, helping to access the resources and boosting knowledge transfer. This chapter analyses the impact of different collaboration ties on the productivity of innovative companies in Belgium, measured in several ways through the innovation survey (Community Innovation Survey) and in terms of patents (Patstat). Patent statistics are used as an objective measure for innovation. Unlike patent data, innovation surveys measure innovation activities carried out in companies. This chapter is primarily concerned with the following research question: do collaboration networks, as measured by innovation surveys (CIS database) and by invention applications (Patstat database), impact productivity growth in the same way? Further, this chapter focuses on an alternative spatial approach in order to look into the role played by proximate and distant inter-organisational networks among organisations. The findings show that the collaboration ties between companies are contributing the most to productivity growth followed by collaboration ties involving universities and government, public or private research institutes. Second, the spatial reach of the inter-organisational networks shows divergent impact on productivity performance of innovating companies.*

***Keywords***: *innovative activities, productivity performance, patent collaboration networks, inter-organisational networks, spatial reach*
***JEL Classification:*** *O12, O34*

## 5.1 Introduction

"A single organisation cannot innovate in isolation" (Dahlander and Gann, 2010, p.699). It has to collaborate with different partners in order to obtain new knowledge and resources and to keep up with competition (Chesbrough, 2003; Laursen and Salter, 2006). Innovation is considered as a problem-solving process, where the solution to a problem is detected through the search engine (Dosi, 1988). The companies, which are involved in forming and maintaining alliances with each other, gain access to information and knowledge directly and/or indirectly (Ahuja, 2000; Gulati and Gargiulo, 1999). The structure of these networks has a strong impact on the dynamics of information diffusion within the networks (Schilling and Phelps, 2007). Direct alliances enable the knowledge flows between partners (Mowery et al. 1996; Gomes-Casseres et al., 2006) and also have an impact on the innovative performance of companies (Deeds and Hill, 1996; Stuart, 2000). Various studies have shown that networks influence company performance and growth (Powell et al., 1996; Powell and Smith-Doerr, 1999). Several empirical studies also highlight the uneven spatial distribution of innovative activities and their networks of partnerships (Hoekman et al., 2013). The key proposition is that collaboration alters the spatial distribution of knowledge, affecting the territorial competitiveness of regions. However, the overlap and relationships with actors outside the region largely remain a black box.

Inter-organisational relations are a crucial aspect of knowledge flows, which are an important engine for innovation. External collaboration is an increasingly important source for companies which makes their boundaries more open for a larger network through which percolates continuous knowledge flows (Ozman, 2009). The definition of open innovation is closely linked with development of collaboration ties of innovating companies with other organisations. These actions are essential for the company in order to develop and absorb new technologies or commercialise new products (Vanhaverbeke, 2006). Companies involved in open innovation are connected with a technology source in order to reinforce their business. The network and company characteristics are two important factors to understand open innovation (Vanhaverbeke, 2006; Chesbrough, 2004). In the literature, inter-organisational networks can be termed in many different ways with a focus on different aspects, but at the same time having a lot in common (Ozman, 2009). For example, in the work of Powell et.al (1996) the authors use the term networks of learning and emphasise the way networks contribute to organisational learning. The term cooperative inter-organisational relationships used by several researchers like Oliver (1990), Ring and Van De Ven (1994), networks of innovators by DeBresson and Amesse (1991), network organisation by Miles and Snow (1986), strategic network by Jarillo (1988) and inter-firm networks by Grandori and Soda (1995).

In recent years the scholars focus on studying a strategic interdependence perspective on alliance formation of business organisations at different levels of analysis. Eisenhardt and Schoonhoven (1996) revealed that companies tend to create new collaboration ties in vulnerable strategic positions when they are competing in the market or because they are trying to develop technical strategies. Other researchers are focused on such parameters as size, age, or financial resources which can influence the tendency of companies to create new strategic ties (Kogut et al., 1992; Barley et al., 1992; Burgers et al., 1993). Gulati (1995) empirically tested the importance of social network and strategic interdependence factors in terms of alliances. The results revealed that social context has an impact on alliances formation between companies, where inter-organisational networks are not only valuable channels for information but also a stimulus for guiding the choice of partners in new ties (Gulati, 1995).

There are many studies which are exploring the motives and reasons of companies to collaborate with other companies. Oliver (1990) in her work emphasises six main motives to collaborate : (i) the need in terms of legal or regularity requirements; (ii) asymmetry, explained as a possibility for an organisation to practice power over another organisation; (iii) reciprocity, presented as opposite to the asymmetry, speak of collaboration; (iv) efficiency, where organisations are trying to increase their output growth; (v) to achieve stability in uncertain environment and (vi) legitimacy, in order to improve reputation, image, prestige. Another way to explain collaborations among organisations is the resource-based approach in terms of the complementarities in organisation resources (Wernerfelt, 1984). According to this view, organisations make alliances in order to reduce uncertainty and to have access to each other's resources (Pfeffer and Salancik, 1978; Hagedoorn, 1993). Organisational learning is also a strong incentive to form alliances among companies in order to explore and exploit knowledge bases (Powell et al., 1996). Spithoven and Teirlinck (2015) reveal that combination of formal and informal network resources positively influence R&D outsourcing intensity.

Several empirical studies indicate that collaboration and geographical proximity are important factors in the diffusion of innovations (Jaffe et al., 1993), helped by knowledge exchange (Gomes-Casseres et al., 2006) and offer information accessibility (Porter 1990). A certain technological proximity between cooperation partners is required, as this technological proximity enhances the likelihood of research cooperation (Cantner and Meder, 2007).

This chapter is primarily concerned with the following research question: do collaboration networks, as measured by innovation surveys (CIS database) and by invention applications (Patstat database), impact productivity growth in the same way? This chapter extends the existing literature in several ways. First, we analyse the impact of different (measurements of) collaboration ties on productivity of innovative companies in Belgium. Second, this chapter uses an alternative spatial approach to look into the role played by proximate and distant inter-organisational networks, measured by different data sources, which in turn broaden the scope and enrich our understanding of collaboration ties.

The remainder of the chapter is organised as follows. Section 5.2 presents a summary of the theoretical and empirical evidence on. the role of inter-organisational networks on performance with respect to the spatial reach of the collaboration network. In Section 5.3 the construction of the database is set out in detail and presents the descriptive statistics. Section 5.4 deals with the specification of the empirical framework and presents the analytical results. Final remarks and avenues for further research are discussed in Section 5.5.

## 5.2 The composition of networks: variety and spatial reach

### 5.2.1 Invention and innovation

What is the difference between the concepts of invention and innovation? Inventions are presented as new ideas, processes or methods, objects that follow from R&D activities at an early stage of development, which can be patented or not. Inventions become innovations when they are commercialised as a product or technology at later stage. As a fact, not all inventions transform into innovations and reach the market. However, both these concepts are used to analyse innovations and their spatial reach. Jaffe and Trajtenberg (1993) analyse the geographic location of patent citations, where the authors found the evidence about geographically localised knowledge spillovers.

Promoting innovation in order to stimulate economic growth is a main concern for public policy. There is an increasing need to measure and assess innovations in order to increase the knowledge about the driving forces behind innovations. Nowadays, publicly available, internationally comparable and reliable data on innovation become accessible. As an example, patent records and innovation surveys data have become relevant indicators of the innovativeness of an economy. R&D expenditure, innovation surveys and patents are three ways to acquire information on the innovative activities of companies. R&D expenditure measures a major input in the innovation process, which is extensively used as proxy for the level of innovative effort. The advantage of this measure is that it is well understood term and it is measured in a quantitative way (OECD, 2005). Patents comprise innovations that are new and worth to be patented, but at the same time might not be introduced on the market. The last source in terms of innovation indicators is innovation surveys. Innovation surveys usually contain qualitative and quantitative data on innovation activities. They are widely used by scholars and policy makers in order to observe and monitor innovation performance (OECD, 2005).

Patent information is a longstanding and increasingly used indicator, to analyse innovation and the innovation process. Patent statistics are often used as an objective measure for innovation. However, patent data do not capture all innovations, but a limited part of it. Some innovations can be considered as not patentable innovation, but at the same time patentable innovations are not patented due to the fact that the company find more efficient ways to protect innovation such as secrecy or the first mover advantage. Based on the empirical evidence the share of patents actually used by companies varies between 40% and 60% of total applications (Scherer et al., 1959; Sirilli, 1987; Napolitano and Sirilli, 1990). Crepon et al. (2000) state that, on average, the percentage of patented innovations in the French industrial manufacturing sector is around 30%. The EPO survey offers very similar results as 47% of companies in the EU used commercially or licensed more than 90% of their patented inventions, and another 16% used between 50% and 90% of their patents (European Patent Office, Utilisation of Patent Protection in Europe, European Patent Office, Munich, 1994).

Quantitative surveys suggest that a large share of companies' inventions is patented. Research carried out by Mansfield (1986) on a sample of US companies showed that companies apply for a patent for about 66-86% of their patentable inventions. This does not mean that patents account for the same share of all inventions, since an unknown number of inventions are not technically patentable. Still, this evidence suggests that companies make use of patenting for the majority of their patentable inventions.

Moreover, Griliches (1990) states that a key problem of patent data as an innovation measure is that inventions which are patented can have differences in their quality. The main problem in the use of patent data is that a patent may never be commercialised which in turn limits patent statistics as a proxy for innovation. However, patent citations are an alternative way of measuring the technological performance of a company.

Unlike patent data, innovation surveys in Europe have been developed from the very beginning with the specific goal of obtaining self-reported information on innovation activities carried out in companies. The innovation surveys gather information on innovators and non-innovators, where 'innovators' are enterprises that over a three years period of time have introduced a new product or a new process. The survey is targeted to a population of companies with ten or more employees and limited to certain economic sectors. These surveys provide data about the inputs, the outputs and the behavioural and organisational dimensions of their innovative activities. The data collected in innovation surveys are predominantly qualitative and subjective. In this context subjective means that they have been build based on the personal appreciation and judgment of the respondents. For example, it is not fully clear what exactly is defined as a new or improved product to the respondents. The difference between the definitions of "new to the firm" and "new to the market" is also subjective. Innovation surveys are presented as cross-sectional data, where the same companies are not necessarily sampled wave after wave. All these features of the data create some difficulties in terms of construction of indicators and the implementation of econometric analyses.

Most of the data from the innovation surveys are qualitative, presented as binary or categorical variables. Such type of data is less informative than quantitative data but is also less affected by measurement errors. Several econometric approaches are used to handle these kinds of data, such as binomial, multinomial and ordered logit and probit models (Mairesse and Mohnen, 2010). The overall input into innovation can be regarded as the sum of R&D expenditure, patent and innovation surveys. However, the data on R&D expenditure is limited to the input side of the innovation process and is, therefore, not used in this chapter which targets the output side: inventions (patents) and innovations (goods and services).

### 5.2.2 The variety in collaborative networks in innovations

Innovation in itself is not done in a vacuum (Pol and Ville, 2009). Collaboration has become an ever more important feature of entrepreneurial strategy to innovate. Complex new technologies very often induce innovative companies to collaborate in order to reduce inherent uncertainties related to innovative products and emerging markets (Vanhaverbeke, and Cloodt, 2006).

Inter-organisational networks among innovative companies play a twofold role: in research and development phases and commercialisation phase of an invention (Vanhaverbeke, and Cloodt, 2006). Network ties can be presented in a formal way such as ventures of R&D partnership, customer-supplier relationship, co-market or develop additional products, or reflect informal collaborations (Simard and West, 2006). These different types of network allow a company to access necessary knowledge very fast with less expenses. Moreover, networks are facilitating the effort to commercialise the new product. Networks are an intrinsic part of any company's environment. Formal or informal networks are the pipeline of the knowledge to a company (Simard and West, 2006).

Inter-organisational networks are closely linked with the idea on open innovation. Coombs (2003) and Howell (2003) use the term 'distributed' innovation; and Chesbrough (2003) refers to 'open' innovation. Inter-organisational networks in the context of open innovation are no longer analysed at the level of a single company but are determined by companies' external relations which are integrated and managed over time (Vanhaverbeke, 2006). Chesbrough (2004: p.23) states that open innovations involve inter-organisational ties to "insource external ideas and to market internal ideas through external market channels".

Inter-organisational networks take on many forms, such as R&D partnership, equity joint ventures, collaborative manufacturing, etc. For example, equity alliances, joint ventures and R&D partnership are categorised as strong ties, while patent agreements, licensing and marketing relations considered as weak ties (Rowley et al., 2000). Weak ties help to get new innovative information, while strong ties create a value through social control and the exchange of tacit knowledge. They show that strong ties have positive relations with performance in steel industry, but in semiconductor industry weak ties are more effective.

The range of empirical studies, where they use patents as a proxy for innovation, are mostly focused on formal ties between different organisations across different industries (Ahuja, 2000; Powell et al., 1996; Walker et al., 1997; Godoe, 2000). Teece (1989) indicates that cooperation increases the knowledge strengthening and decrease the chances of duplicates which in turn increase patenting rates (Almeida and Kogut 1999; Baum et al, 2000). In general, network ties positively influence innovation activity of companies (Shan et al., 1994; Powell et al., 1999; Baum et al. 2000). Other scholars emphasis that companies which are involved in multiple types of ties are more innovative in contrast to those which have only one type of tie (Powell et al., 1999; Baum et al., 2000). Shan, et al. (1994) analysed cooperative relationships of start-up companies in biotechnology and concluded that cooperative relations explain innovative output. Similar work conducted by Stuart (2000), who analyses innovation activities in the semiconductor industry, emphasises that patenting activity of young and small companies are increasing if the companies have technologically sophisticated alliance partners which might be located abroad. Baum et al. (2000) focus on 142 start-up companies' alliances in biotechnology industry and how these collaborations affect the performance. The results show a negative impact on innovation if direct competitors were involved in the alliance. Stuart (2000) emphasises the importance of patenting in forming an alliance. The author states that companies with many prior patents tend to have more alliances than companies lacking such patents. Sarkar et al., (2001) state that younger and smaller companies get more benefits from collaboration networks than large companies, due to the uncertainty of the technological landscape. All cited studies have been carried out based on patents as indicator of innovation activity and knowledge development (Griliches, 1998).

The importance of inter-organisational networks is further stressed from different perspectives over recent decades. Network ties facilitate company's innovative capabilities by opening up new sources for innovations, access valuable resources, and boosting knowledge transfer. Formal and informal collaborations provide the possibilities for companies to succeed in their objectives they could not reach alone. Dyer and Singh (1997) distinguish four sources of competitive advantage in inter-organisational collaboration: development of relationship-specific assets, mutual learning and knowledge sharing, combining complementary features, and lower transaction costs following from superior governance structures.

The innovative capabilities of companies can be improved through development of inter-organisational collaborations with a variety of partners. Inter-organisational collaboration provides the access to additional assets which can help in commercialisation of the innovative project (Hagedoorn, 1993; Teece, 1986) and help to spread the costs and risks of research and development among different organisations (Hagedoorn, 2002; Veugelers, 1998). Several studies suggest that not all alliances are successful, where up to 60 % of collaborations failed (Bleeke and Ernst, 1993; Harrigan, 1986). Often mentioned reasons for failure of the alliance are unintended knowledge spillovers (Teece, 2002; Veugelers, 1998), try to win the internal "race to learn" among the partners (Larsson et al., 1998), and the absence of flexibility and adaptability (Doz, 1996; Ring and Van de Ven, 1994).

It is well known that performance data is difficult to access and to interpret it. Management scholars and economists contributed in developing a knowledge-based theory of companies (Cohen and Levinthal 1990; Kogut and Zander 1992; Powell et al 1996). Grant (1997) developed the fundamentals of a knowledge-based theory, which explains the rationale for the company, the differentiation of its boundaries, the origin of organisational capacity, the distribution of decision-making authority and the determinants of strategic alliances. The author states that collaboration agreements enable to use internal knowledge resources and divert long-time lags in developing new capabilities internally. For example, Burt (1992) investigated the relationship between corporate profit margins and the positions of markets in networks of interindustry buyer-seller transactions. Baum et al. (2000) argued that that the diversity of the company's alliance network has an impact on the innovative performance of the company. Empirical studies emphasise that most of collaborations are of short duration and unsuccessful, in a way to achieve their aims in terms of R&D innovation, organisational knowledge, or foreign-market diffusion (Todeva and Knoke, 2005). From other point of view, cooperation in innovation activities is often pursued by enterprises to share knowledge, to benefit from complementarities, to reduce risk or to save on costs. A large number of studies have examined the determinants of cooperation in general and with different partners in particular. Many authors conclude that firms which collaborate tend to spend more on R&D (Kaiser, 2002; Tether, 2002; Miotti and Sachwald, 2002; Belderbos et al., 2004).

The analysis and measurement of the productivity effects of innovation activities has been one the most challenging and controversial tasks in empirical economics (Griliches, 1979; Griliches and Pakes, 1980).Taking advantage of the innovation surveys for France, Crépon, Duguet, and Mairesse (1998) conclude that firm productivity correlates positively with a higher innovation output. Other European studies based on innovation surveys reported similar results for other industrialized countries (e.g., see Loof and Heshmati, 2002; Loof et al., 2003; Van Leeuwen and Klomp, 2006). The relationship between innovating activities and patenting practices has been examined by several researchers. Pakes and Griliches (1984) and Bound et al. (1984) reveal a strong relationship between R&D spending and the number of patents. Acs and Audretsch (1990) reveal that the relationship between a firm's involved in R&D spending and patenting activities is more complicated and conclude that firms have decreasing returns to their R&D spending.

From the discussion above, the following hypotheses are formulated:
**H1a:** Innovative companies that have a larger variety of inter-organisational collaborative types of partners have a higher productivity performance.
**H1b:** Inventive companies that have a large variety of inter-organisational collaborative types of partners have a higher productivity performance, but not different from innovative companies without patents.

### 5.2.3 The spatial reach of collaborative networks in innovation

The location of knowledge production and the characteristics of knowledge diffusion becomes a crucial issue in understanding economic development (Acs et al. 2002). Varga (1999) and Caniëls (2000) state that production of new scientific and technical knowledge has a prevailing tendency to cluster spatially. Using patent information, Jaffe et al. (1993) demonstrated that knowledge spillovers are spatially concentrated. The resource-based view predicts that, when companies are sourcing new knowledge and technology, they will aim to acquire it irrespective of the location (Spithoven and Teirlinck 2015), whether or not enhanced by institutional, cognitive or social proximity (Boschma 2005). The performance in terms of productivity growth is expected to differ substantially according to the region in which the company is located. Vinding (2002) finds that domestic partners have a better impact on innovation performance of Danish manufacturing companies than foreign partners, which can be explained by the higher costs related to the distance. Essentially, spatial proximity plays an important role in facilitating knowledge flows between actors in a system of innovation.

According to the taxonomy of network ties from Simard and West (2006), innovative companies have to combine 'deep' and 'wide' ties. The knowledge contained in deep ties is easily activated and captured, where the access to the knowledge is enhanced by spatial co-location. Wide ties give the access to non-redundant information. They are also more difficult to manage in terms of capturing new knowledge. These ties are spatially diversified and enable companies to connect and exploit important resources for innovation in terms of deep ties and investigate new technologies in wide ties. Scholars argued that these two types of ties are based on different models of inter-organisational knowledge flows and can contribute to different forms of innovation (Chiang and Hung, 2010).

From the position of network theory, geography plays a role of an external variable which is a part of the contextuality of the network (Glückler, 2013). Gittelman (2007) states that the institutional field of knowledge creation, including the open scientific community or the commercial domain, has less impact of geographic proximity on its following acceptance. Bell and Zaheer (2007) posit that knowledge is sourced from other organisations and from different spatial levels via collaborative networks. They, first, put forward that there is not much known about the different types of ties, claiming that linkages involving individuals are superior to others, irrespective of the spatial reach. Second, they emphasize that the regional context itself remains crucial for the existence of collaborative networks.

Therefore, the following is hypothesized:
**H2a:** The spatial reach of innovative companies that engage in a variety of inter-organisational collaborative types of partners have a higher impact on productivity performance.
**H2b:** The spatial reach of inventive companies that engage in a variety of inter-organisational collaborative types of partners have a higher impact on productivity performance, but not different from innovative companies without patents.

## 5.3 Data and estimation strategy

### 5.3.1 Database construction

The primary data are drawn from the Community Innovation Survey 2014 (CIS) for Belgium. This survey collects information on the company's innovation activities in Belgium during the three years 2012 to 2014 inclusive. This cross-sectional dataset contains 4,118 companies. An important feature of the surveys is that the questionnaires are sent to the companies with at least 10 employees. The survey provides information on companies' innovation activities including the acquisition of machinery, equipment, buildings, software, and licenses; engineering and development work, feasibility studies, design, training, R&D and marketing when they are specifically undertaken to develop and/or implement a product or process innovation. This includes also all types of research and development (R&D) activities to create new knowledge or solve scientific or technical problems. These data are matched with financial data on net added value, employment and sector (ISIC or NACEBEL codes) from a firm -level financial database (BELFIRST, 97% are matched). BELFIRST gathers detailed information on companies in Belgium (2014). All monetary variables, expressed in current prices, are transformed in constant prices using the GDP deflator (base=2010).

Next, this CIS database is matched with the patent data using the names of the companies in Belgium, because patent data does not contain VAT numbers which usually serve as an unique identifier of companies. The patent information is retrieved from the PATSTAT raw data which contains inventor information with country and city names and applicant information (version 14.24 PATSTAT Biblio, Edition 2016 - Autumn). PATSTAT contains bibliographical information and the legal status of patent documents granted in more than 100 patent offices worldwide. As a search engine we used the country name – Belgium – where at least one assignee is located in Belgium. The datamining process identified 34,810 Belgian first filled patent applicants (excluding duplicates within the same family group) covering the period 2000-2013. During the data selection process, we dropped all patents if the type of organisation – company, government organisation, non-profit organisation, university or hospital – could not be identified after additional cleaning and if the names of different organisations were missing.

Some issues with patent data are detected during its processing. First, identification of the type of organisation is not always correct in the original patent dataset. Every organisation is manually checked. If the organisation of an applicant could not be determined, then it is classified as unknown. Second, names of organisations can have different spellings which are identified through manual cleaning. Such cleaning procedures are necessary in order to be able match patent data with financial information and CIS dataset.

In total, 370 CIS companies are involved in patenting activities after matching CIS and PATSTAT databases. In addition, we have adapted the patent sample in CIS to the style of the Community Innovation Survey, where we constructed the same variables for further comparison. First, three types of co-applied partners between different organisations among applicants are identified: (i) company innovating with other companies (COMP); (ii) company with Universities or other higher education institutes (UNI); and (iii) company with Government, public or private research institutes (GOV).

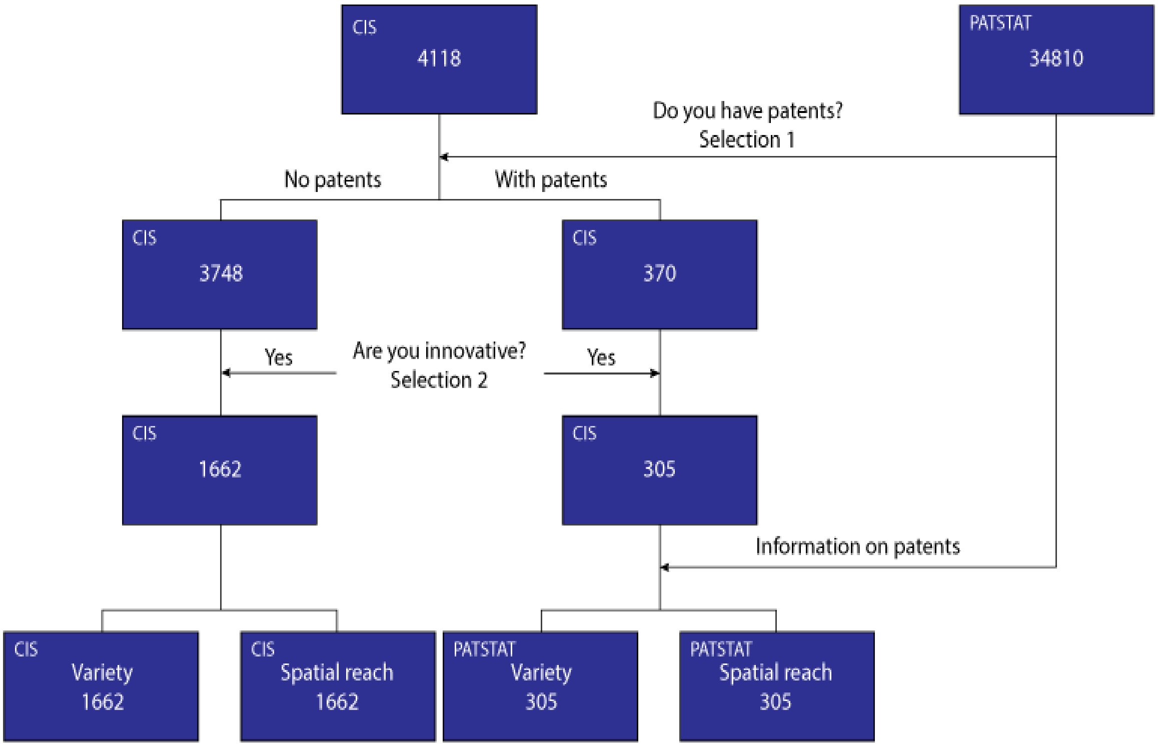
Second, using a similar approach as Bergek and Bruzelius (2010), we develop a detailed classification based on the co-applied patent partnership by location. If a patent application is the result of a co-applied partnership with multiple inventors residing in one or more countries, it is possible to identify a range of spatial levels on which patent collaboration occurs in co-applied patent partnership. This is called the 'spatial reach' of co-applied patents. This approach includes (i) patent collaboration exclusively with domestic inventors from Belgium (BE); (ii) patent collaboration exclusively with European inventors (EU); (iii) patent collaboration exclusively with US inventors (US); (iv) patent collaboration exclusively with Chinese or Indian inventors (CI); and (v) patent collaboration exclusively with inventors from all other countries (OC).

Third, we distinguish process innovation from product innovation in patent sample. Each time the word "process" and/or "method" are found in the title of patent application, the patent application is assigned to a process invention. Further, in Figure V-1 we illustrate the steps of obtaining the databases.

Our subject is the Community Innovation Survey, a relatively new source that has its advantages and disadvantages and Patent database from Patstat which is an ideal setting for our investigation. The combination of both sources can provide a clear vision on inter-organisational networks and their impact on productivity performance.

Summarising, our primary dataset consists of 4,118 companies in Belgium in terms of innovations and innovation activities during the three years 2012 – 2014 including financial information from Belfirst. Next, the dataset is merged with patent data from PATSTAT, where 370 CIS companies have patents. This dataset contains information on co-application partners and their spatial reach. Based on our primary dataset, we extracted two other datasets for further analysis. The second dataset includes only those innovative and non-innovative CIS companies which do not indicate any patenting activities (3,748 companies) and the third dataset consists only those innovative and non-innovative CIS company which reveal only patenting activity (370 companies) with the same set of variables on co-application partners and their spatial reach as in previous databases, which only constructed based on patent information. For further analysis we consider only innovative CIS companies, where second dataset consists 1,662 observations and the third dataset includes 305 CIS companies.

**Figure V-1. Structure of CIS and patent databases used in the analysis.**




Source: own elaboration.
Note: T-statistic has been produced for CIS firms which reveal patenting activity (305), in order to identify if there is a difference between variables constructed based on CIS and PATSTAT approaches. The output provides useful descriptive statistics and states that the group means are significantly different as the p-value is less than 0.05 for different collaboration ties as well as for spatial reach.

## 5.3.2 Econometric framework

We took productivity performance of companies in Belgium in the sample for 2014 as the dependent variable.

$$Y_i = e^{a} S_i^{b} e^{\varepsilon_i} \qquad (i=1,\dots,I) \quad (1)$$

where Y is output in terms of productivity. The dependent variable productivity is presented as value added of a company i divided by the number of employees of that company; S is the size of the company, measured by number of employees; *a* and *b* represent the elasticities of output with respect to each of the inputs; $e^{\varepsilon_i}$ is an error term, and the subscript i refers to the observation number and indicates a company in cross-section data.

The following linear relationship is estimated, we transformed Eq. (1) to natural logarithms and estimated the elasticities *a* and *b*:

$$y_i = a + b_1 s_i + \varepsilon_i \qquad (2)$$

In addition to the basic equation we also added the age of company, breadth of collaboration of company, industry dummies, regional dummies, number of patents produced by company and patenting activity of company. The breadth variable is empirically linked with innovative performance, exploring how differences in search strategies (wide and deep open search strategies) among companies impact their ability to get different levels of originality in their innovative activities (Laursen, and Salter, 2006). This independent variable is constructed using the number of collaborations a company has.

Further, the analysis of productivity is extended by implementing, first, the collaboration pattern of the innovative companies from the CIS database. More detail, we test the type of collaboration partners of the company: (i) with other companies (COMP); (ii) with universities or other higher education institutes (UNI); and (iii) with government, public (or private) research institutes (GOV). The second extension tests collaboration within CIS companies which do not have any patenting activities. And the last, the same collaboration variables with the type of collaboration partners are constructed for the patent sample in CIS database. Two equations are estimated, expanding the baseline equation (2) adding collaboration partner types (COMP, UNI, and GOV) as independent variables for three types of developed datasets: CIS, CIS without patent sample from PATSTAT, and only CIS companies which indicate patent activities.

$$y_i = \alpha + \beta_1 s_i + \gamma_1 COMP_i + \gamma_2 UNI_i + \gamma_3 GOV_i + \varepsilon_i \qquad (3)$$

In equation 3 $COMP_i$, $UNI_i$ *and* $GOV_i$ refers to the collaboration activity of company i. The variables take the value of 1 if a company collaborates with another company, or university or other higher education institute, or government, public or private research institute, and 0 otherwise in CIS and Patstat databases. Further, all independent variables are categorised by the type of innovation (process or product). Additionally, we include industry dummy variables, the age of a company i, breadth, number of patents produced by a company i and patenting activity of a company i, classification by the type of innovation (product innovations are chosen as process innovations are generally less likely to be patented), and region dummies, to control for different productivity effects across the three regions in Belgium: the Brussels-Capital Region, the Flemish Region, and the Walloon Region.

We extend our research in order to examine the collaboration pattern, in a more detailed way by taking the spatial reach of the type of collaboration partners into account. Therefore, we include in the baseline equation the variables on the spatial reach of the network for three types of datasets.

$$y_i = \alpha + \beta_1 s_i + \gamma_4 BE_i + \gamma_5 EU_i + \gamma_6 US_i + \gamma_7 CI_i + \gamma_8 OC_i + \varepsilon_i \qquad (4)$$

These independent variables covering the spatial reach take the value of 1 if collaboration only within domestic companies from Belgium (BE); (ii) with European companies (EU); (iii) with US companies (US); (iv) with Chinese or Indian companies (CI); and (v) with companies from all other countries (OC), and 0 otherwise in CIS and Patstat databases. The descriptive statistics and variables' definitions are provided in Appendix III-1 (Tables 1.1-1.3).

The cross-sectional method is the predominant mode of analysis in empirical research. Despite its broad usage, the issue of parameter variation and the associated limitations of cross-sectional methods have received little attention in the empirical literature. For example, Bergh (1995:) indicates in his research on diversification and performance that 'researchers have not included time-related change in their empirical models, either as a structural component or as a factor.' Lubatkin and Chatterjee (1991) mentioned that the usage of a single year in cross-sectional data hinders researchers from accounting for any trend effects in their research.

Similarly, Rumelt (1991) notes that reliance on a single year of data may fail to identify the correct pattern, if any, of the relationship investigated. In the study of Hill and Hansen (1991), the authors state that the cross-sectional studies may experience an inability to identify causality. Most of the researchers still have an issue to test the stability of their empirical relationships over time despite the increasing use of longitudinal studies (Bergh and Holbein, 1997).

## 5.4 Empirical analysis and results

### 5.4.1 Collaboration on innovation

In this section, we empirically examine if different collaboration ties measured by Innovation Survey and Patent databases impact productivity the same way. Collaboration is an important aspect of innovative activity, because the information exchange reinforces the discussion and the production of new knowledge (Katz and Martin, 1997; Heinze and Kuhlmann, 2008; Ortega, 2011). The productivity performance of innovative companies is calculated for 2014 and shown in Table V-1. The dependent variable in the analysis is presented by the productivity performance, in terms of value added of a company divided by a number of employees. Ordinary least square (OLS) is used to estimate the importance of various determinants of the company's productivity performance.

It is very common that the companies tend to cooperate more with other companies than with universities for example. Fritsch and Lukas (2001) analyse 1,800 German companies, where 33% of companies do cooperate with public research centres, 60% with customers, 49% with suppliers and 31% with other companies. On contrary, in the work of Gemunden et al., (1992), where 800 German manufacturing companies were investigated, the authors find that almost a third collaborate with universities and research centres, while 21% are engaged in R&D cooperation with other companies.

Model 1 with innovators includes only the breadth variable which is empirically linked with innovative performance and constructed based on the number of collaborations firm has. We find positive significance of the breadth variable in our analysis with CIS companies which do not indicate any patenting activities.

The results in Table V-1, Model 2 suggest that knowledge flows through collaboration ties with other companies, measured by CIS, are meaningful, because the coefficient of COMP indicates a positive and significant effect on the company's productivity performance. Such outcome is not surprising as collaboration involves two or more independent companies working together can achieve greater success than can be managed in isolation (Daugherty et al., 2006). However, the success rate of such collaborations is not very high, De Man and Duysters (2005) indicate mortality rate between 50% to 70% of collaboration alliances among companies.

The OLS regression in Model 2 points to a significant impact on productivity performance when the collaboration is with universities. The findings by many researchers indicate a substantial increase in the collaborations between companies and universities in European Union countries (e.g. Barrett et al., 2000; Gertner et al., 2011; Powers, 2003). In the work of

Arora and Gambardella (1994), the authors reveal that business-university collaboration ties play a role of a risky asset and suppose to last much longer than collaborations between companies. The facilitation of such collaborations can be also explained by the fact that universities are altering their approach in terms of carrying out more applied research, which is in turn demanded by the business sector (OECD, 1998; Santoro and Chakrabarti, 1999).

**Table V-1. The impact of different collaboration ties on productivity performance of innovative companies measured through CIS and Patent databases**

| OLS, robust | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| *Size (s)* | -0,038 | -0,04 | 0.112*** | 0.118*** |
| | (0.069) | (0.067) | (0.040) | -0,041 |
| *age2014* | 0,002 | 0.001 | 0.001 | 0,001 |
| | (0.0010) | (0.001) | (0.001) | -0,001 |
| COMP | | 0.117*** | | 0.232** |
| | | (0.026) | | -0,099 |
| UNI | | 0.112*** | | 0.460* |
| | | (0.036) | | (0.237) |
| GOV | | -0.060 | | |
| | | (0.041) | | |
| breadth | 0.027*** | | 0.168** | |
| | (0.010) | | (0.076) | |
| num_patents/Size | | | 1.362*** | 1.443*** |
| | | | (0.520) | (0.524) |
| product | -0.029 | -0.037 | 0.048 | 0,02 |
| | (0.030) | (0.030) | (0.0993) | -0,098 |
| IMR | -0.610 | -0.609 | 0.194 | 0.121 |
| | (0.437) | (0.432) | (0.471) | (0.454) |
| *Industry dummies* | yes | yes | yes | yes |
| *Region dummies* | yes | yes | yes | yes |
| *R-squared* | 0.129 | 0,139 | 0.173 | 0.176 |
| *Prob > F* | 0 | 0 | 0 | 0 |
| *N* | 1662 | 1662 | 305 | 305 |

Model (1-2) includes only those CIS companies which do not indicate any patenting activities.
Model (3-4) consists only those CIS companies which reveal patenting activity.
Notes: * significant at the 10% level of significance; ** significant at the 5% level of significance; *** significant at the 1% level of significance.

In respect to the collaboration ties with government, public or private research institutes, the results do not indicate any importance when the database includes only CIS companies without any patenting.

Model 3 with inventing innovators, which includes the breadth variable as in Model 1, indicates positive significance of the breadth variable in our analysis for those CIS firms which reveal patenting activity. The results in Model 4 suggest that knowledge flows through collaboration ties with other companies, measured by Patent databases, are meaningful and have a positive and significant effect on the company's productivity performance. When the company has university collaboration ties the results indicate significance at the 10% level of significance on productivity performance. With respect to the collaboration ties between company and government public (or private) research institutes, we could not identify any collaboration ties, due to limited number of observations. In addition, Model 4 shows that the coefficient on number of patents is positive and statistically significant, suggesting that patenting activities in general positively influences productivity performance. Such outcome is not surprising, since Scherer (1965), considering 365 of the largest US corporations, observes that inventions, measured by patents, have a positive effect on company profits via sales growth. The research of Bloom and Van Reenen (2002) states that patents have an economically and statistically significant impact on company-level productivity, where citation-weighted patent stock increases total factor productivity by 3%. Laursen and Salter (2006) state that companies who are more open to external sources or search channels indicate a higher level of innovative performance.

The results from Model 1 and Model 3 corroborate with the Model 2 and 4. The inclusion of the breadth variable together with collaboration variables do not show any importance due to multicollinearity issue, arisen from the way of construction of the variables. Similar impact on the company's productivity performance is also observed between Model 2 and Model 4 when the collaboration ties involve other companies and universities.

Hypotheses H1a and H1b are fully confirmed in this analysis. Innovative companies that engage in a variety of inter-organisational collaborative types of partners indicate a higher productivity performance and have the same impact on productivity performance if measured through CIS or Patstat datasets.

Alternative methods are used to examine the robustness of the results. Selection problems occur in a wide range of applications in econometrics. The main problem arises from the sample selection where a sample can be unrepresentative of the population we are interested in. Thus, we are using a two-stage estimation procedure proposed by Heckman (1979), the inverse Mills ratio (IMR) to correct for the selection bias in all Models. The method consists two steps. In the first step, a regression is modelled with a probit model for observing a positive outcome of the dependant variable (see Appendix III-2, Table 2.1). In the second step, the inverse Mills ratio is generated from the estimation of a Probit model, where the Probit model assumes that the error term follows a standard normal distribution. The inverse Mill ratio was included as an additional explanatory variable in the OLS to explain the variation in productivity performance in Model 1-4. We note that the inverse Mills ratio is never significant in these estimates. Thus, although it is correct to take account of possible sample selection bias, there is no evidence that such bias is a significant problem.

In addition, we are also using three-stage least square (3SLS) approach. This procedure is ideal for dealing with the simultaneous effects of the explanatory variables with the error term in our model as it handles both the endogeneity of the innovation variables as well as the possibility of correlated errors between variables. 3SLS is seen as a special case of multi-equation GMM where the set of instrumental variables is common to all equations. The results do not indicate any possible unobserved companies' fixed effects (Appendix III-2).

### 5.4.2 Network spatial reach on innovation

Analysing inter-organisational networks and their spatial reach broadens the scope and enriches an understanding of collaboration ties. Table V-2 explores the impact of the spatial reach of the different collaboration ties among innovative companies on productivity performance. Table V-2 provides information on the most successful type of spatial reach (national, European, US, Chinese and/or Indian, other international) of collaboration network and its impact on the company's productivity performance.

The results in Table V-2 introduce a secondary spatial dimension in terms of the spatial reach: Belgium, EU, USA, China/India and other countries. Collaborations ties involving a company and another company at the Belgian level, the OLS regressions indicates non-significant impact on productivity for both datasets (Model 5 and 6). A spatial reach with other EU countries indicates meaningful results only in Model 5, when patenting collaborations are involved the results are not significant. At the USA level the results are positive and significant when the patenting activity presents. For China/India spatial reach the results do not indicate any importance in both Models. At the USA level the results are stronger when the patenting activity presents. These results confirm the findings of Guellec and van Pottelsberghe de la Potterie (2000), who assess, using granted EPO patents, the extent to which some attributes of a patent are related to its value. They posit that "International co-operation seems even more fruitful than domestic co-operation" (Guellec and van Pottelsberghe de la Potterie 2000, p.112). Similar results are found by Cincera et al. (2003) who focus on the role of knowledge in explaining the performance at the company level, by augmenting the classic productivity growth approach with R&D cooperation. Their findings confirm the positive effect of foreign cooperation on sales growth and indicate a significantly negative influence on sales growth by interaction term with national R&D cooperation (Cincera et al. 2003). Similarly, Archibugi and Pianta (1996) conclude that international patent collaborations are revealed in the rapid growth of patents with inventors from different countries.

With respect to the collaboration ties with universities, the spatial reach at the Belgian level indicates significant impact on productivity for Model 5 only. For Model 6, where involved only those CIS companies which indicate patenting activity, the outcome does not indicate any importance. The spatial reach with other EU countries shows positive and significant results for the Model 5. Such results can be explained by the fact that when businesses and universities are situated in the same geographical area, the political or economic issues unite them (Mansfield and Lee, 1996), the geographical proximity play an important role in such types of collaborations.

Further, the econometric analysis which tests the impact on productivity performance involving company-government spatial reach do not indicate any importance. There is no significant result found in collaboration ties with government for Model 5. Model 6 reveals some limitations in terms of no data availability for this type of spatial reach.

Ramsey RESET test has been applied as general specification test for the linear regression model. The Model 5 and 6 do not suffer from omitted variable as Ramsey RESET test indicates Prob > F = 0.24 and F =0.48. A link test also used. This test can be run after any single-equation estimation command. The test is based on the idea that if a regression-like equation is properly specified no additional independent variables should be significant above chance. The link test looks for a specific type of specification error called a link error wherein, a dependent variable needs to be transformed to accurately relate to independent variable. The t-test statistics for Link test is insignificant in both Models, indicating that the models are fixed and pass the link test (see Appendix III-3). In addition, we applied a two-stage estimation procedure, the inverse Mills ratio (IMR). The results in both models are insignificant. Three-stage least square (3SLS) approach have not indicated any possible unobserved companies' fixed effects as well.

**Table V-2. The spatial reach of the collaboration ties on productivity performance of innovative companies measured through CIS and Patent databases**

| | **OLS** | **Model 5** | **Model 6** |
|---|---|---|---|
| | *Size (s)* | -0.051 | 0.106*** |
| | | (0.070) | (0.041) |
| | *age2014* | 0.002 | 0.001 |
| | | (0.001) | (0.001) |
| COMP | BE | -0.045 | 0.111 |
| | | (0.031) | (0.084) |
| | EU | 0.096*** | 0.148 |
| | | (0.032) | (0.260) |
| | USA | 0.055 | 0.919*** |
| | | (0.056) | (0.266) |
| | CI | -0.025 | 0.382 |
| | | (0.066) | (0.326) |
| | OC | 0.113* | 0.144 |
| | | (0.060) | (0.198) |
| UNI | BE | 0.097** | 0.060 |
| | | (0.039) | (0.303) |
| | EU | 0.148** | |
| | | (0.064) | |
| | USA | -0.041 | |
| | | (0.218) | |
| | CI | -0.130 | |
| | | (0.335) | |
| | OC | 0.105 | |
| | | (0.370) | |
| GOV | BE | -0.058 | |
| | | (0.043) | |
| | EU | -0.087 | |
| | | (0.082) | |
| | USA | 0.092 | |
| | | (0.352) | |
| | CI | -0.205 | |
| | | (0.696) | |
| | OC | -0.738 | |
| | | (0.642) | |
| | num_patents | | 1.273** |
| | | | (0.530) |
| | product | -0.041 | 0.037 |
| | | (0.030) | (0.102) |
| | IMR | -0.664 | 0.257 |
| | | (0.441) | (0.444) |
| | *Industry dummies* | yes | yes |

| OLS | Model 5 | Model 6 |
|---|---|---|
| *Region dummies* | yes | yes |
| *R-squared* | 0.147 | 0.195 |
| *Prob > F* | 0.00 | 0.00 |
| *N* | 1662 | 305 |

Model 5 includes only those CIS companies which do not indicate any patenting activities
Model 6 consists only those CIS companies which reveal patenting activity
Notes: * significant at the 10% level of significance; ** significant at the 5% level of significance; *** significant at the 1% level of significance.

In summary, the collaboration ties between companies are the most contributing to productivity performance followed by collaboration ties involving universities. The government public or private research institutes collaboration ties do not indicate any importance. Concerning the spatial reach between companies' collaboration partnership, the productivity of the Belgian companies indicates positive and significant outcome when international (EU and non-EU) spatial reach is involved. Both datasets constructed from CIS and Patstat reveal similar trends in terms of spatial reach, where the CIS sample emphasis more international impact through EU and other countries and Patstat sample in turn highlights the importance of USA based international spatial reach.

The collaboration ties with universities have a stronger impact on the productivity performance when the Belgian and other EU countries' spatial reach is involved, meanwhile the international (non-EU) collaborations do not indicate any importance. The productivity performance of the weakest collaboration tie between companies and government, public or private research institutes doesn't show any significant impact at any spatial reach level. This outcome is not surprising, as the distribution of Public-Private-Partnerships between business and government cooperation is skewed across the different regions of Belgium, due to the absence of a national policy. Only the Flemish region has an official policy (Akintoye et al., 2002).

In conclusion, the postulated hypothesis H2a and H2b are partially confirmed: the spatial reach of innovative companies that engage in a variety of inter-organisational collaborative types of partners is more effective in terms of productivity performance if measured through CIS. And H2b cannot be fully compared due to limitations in the number of observations of constructed databases.

## 5.5 Conclusions

This study offers additional evidence to confirm the prevalent assumption that collaboration ties can influence performance. Scholars in the innovation and inter-organisational learning works have reasoned that linkages and the collaboration networks provide the access to external knowledge (Powell et al, 1996). The limited empirical evidence on characteristics of collaboration ties that influence performance has prevented researchers from understanding which collaboration ties contribute most to company productivity performance and in general how companies can best use collaborations as part of their knowledge creation strategies. Although prior work has shown that collaborations do matter for company performance (e.g., Ahuja, 2000), the current research demonstrates that some collaboration ties contribute more than others and investigates further spatial reach factors.

The analyses conducted in this study confirm the hypotheses outlined. The different collaboration ties measured by CIS and Patent databases show that the performance of the Belgian innovative companies is enhancing. We analysed this issue with inter-organisational collaboration data from CIS and patent data from Patstat covering 2014. The effects of collaboration network position on performance are rather beneficial. These findings showcase that collaborative ties might be the potentil opportunities for learning and innovation. Controlling for other explanations, age has not indicated the impact in our analysis. Similar results were found by Powel et al. (1996) where the authors explain this fact as companies do not avoid collaborations as they grow older, and the size has no predictive influence on productivity.

The most interesting ancillary finding is that the collaboration ties between companies are the most contributing followed by collaboration ties involving universities and government, public or private research institutes. The dataset which consists only those CIS innovative companies with patenting activity indicated similar outcome for the collaboration ties between companies and followed by universities. However, some limitations have been encountered, the collaboration ties with government, public or private research institutes were not found in patent sample with CIS innovative companies, which in turn prevented our analysis to make a comparison with CIS database where companies are not involved in patent activities.

This study's findings reffer that companies likly should consider the idea of inter-organisational arrangements in order to increase the effectiveness in terms of productivity performance. It was observed during this study that inter-organisational collaboration with different partners (with other companies, universities and government, public or private research institutes) contributes to the productivity performance of companies, while, at the same time, the observed relationships differ from each other and indicate the different impact level on productivity performance. These results highlight the possibility for senior management of adopting an approach to inter-organisational collaborations, involving innovations and patenting activities, in order to potentially improve the outcomes in terms of developing existing technologies and creating new ones. Such inter-organisational ties might result in the creation and development of resources (Das and Teng, 2000), might help to spread the costs of research and development (Veugelers, 1998; Hagedoorn, 2002), and at the same time might reduce the risks associated with innovations.

Another implication of this study that merits emphasis is the analysis of inter-organisational networks and their spatial reach which enlarge our understanding of collaboration ties. The secondary spatial dimension in terms of the spatial reach is presented through Belgium, EU, USA, China/India and other countries. Considering innovative companies sample the results are the following:

Collaborations between companies at different spatial levels have a relatively significant impact on productivity only in case when international spatial reach is involved both in terms of innovations and patent collaborations, where the CIS sample emphasis more international impact through EU and other countries and Patstat sample in turn highlights the importance of USA based international spatial reach. The collaboration ties with universities have a relatively stronger impact on the productivity performance when the Belgian and other EU countries' spatial reach is involved. Additionally, the results show that the international (non-EU) collaborations do not have any impact. Collaboration between companies and government, public or private research institutes doesn't show any significant impact at any spatial reach level on productivity performance of the companies. The outlined hypothesises were partially confirmed in this part of the analysis.

The results of our analysis also raise a number of questions and limitations, which suggest appropriate actions for further research. First, due to data availability, this research only adopts one outcome where CIS database for one period of time is used. Having panel data would be desirable because it rules outfixed effects possibly affecting the results to some extent as well as will help to avoid possible endogeneity problems. Future studies could utilize more recent years, to confirm the results. Moreover, the dynamic evaluation might present a more comprehensive picture of the collaboration ties performance. Further studies could conduct a comparative analysis to account for the effect. Meanwhile, including sectoral analysis with the updated and elaborated dataset can bring additional insights to the research.

A problem that is appearing in this research is the lack of an indicator of the scale or number of collaborative innovative activities of each type in the European Community Innovation survey data used here. To examine accurately the impact of innovative inter-organisational collaborations on productivity performance for Belgian companies, information on the number and importance of such ties may be crucial. Here an alternative approach would be to utilise databases on innovative inter-organisational collaborations that have been the subject of analysis in most of the management literature.

The presented results highlight the need for further research. First, the mix of collaboration ties and their contribution to the productivity performance must be investigated further. This article has presented some preliminary evidence but also has highlighted some of the problems in the present approach. The future research could contribute by examining how particular inter-organisational ties have an effect in longer term. The possible expansion of the database can also allow to analysis and compare in detail the spatial reach of the collaborations ties which involve government, public or private research institutes.

## Appendix III

### Appendix III-1 Variable definition and descriptive statistics

### 1.1 Survey variables

*y:* logarithm of the output growth, measured in terms of productivity, 2014
*s:* logarithm of the size of the company, measured by number of employees
Table 1.1 provides information about the constructed variables for the type of collaboration ties divided into three categories.

**Table 1.1 Variables constructed**

| Variable | Description | Explanation | | |
|---|---|---|---|---|
| | | CIS (primary dataset) | CIS companies without any patenting activities | CIS companies with patenting activity only |
| COMP | company with other companies | Presented as a dummy variable | Presented as a dummy variable | Presented as a dummy variable |
| UNI | company with universities or other higher education institutes | | | |
| GOV | company with government, public or private research institutes | | | |

Table 1.2 provides information about the constructed variables for the spatial reach divided into five categories.

**Table 1.2 Variables constructed**

| Variable | Description | Explanation | | |
|---|---|---|---|---|
| | | CIS (primary dataset) | CIS companies without any patenting activities | CIS companies with patenting activity only |
| *BE* | Only collaboration within Belgian companies (CIS)/inventors (PATSTAT) | Presented as a dummy variable; variables are available in the CIS database | Presented as a dummy variable; variables are available in the CIS database | Presented as a dummy variable; variables are constructed from patent databased by the same principle as in CIS |
| *EU* | Only collaboration within European companies (CIS)/inventors (PATSTAT) | | | |
| *USA* | Only collaboration within American companies (CIS)/inventors (PATSTAT) | | | |
| *CI* | Only collaboration within Chinese or Indian companies (CIS)/inventors (PATSTAT) | | | |
| *OC* | Only collaboration from all other countries companies (CIS)/inventors (PATSTAT) | | | |

**Table 1.3a Descriptive statistics for CIS (primary dataset)**

| | CIS (primary dataset) | | | | | |
|---|---|---|---|---|---|---|
| | Variable | Obs | Mean | Std. Dev. | Min | Max |
| | y (productivity) | 4118 | 4.339 | 0.556 | 0.135 | 8.060 |
| | s (size) | 4118 | 3.748 | 1.122 | 1.386 | 10.443 |
| | age | 4118 | 28.324 | 18.899 | 0 | 152 |
| | Types of collaboration ties | | | | | |
| | COMP | 4118 | 0.254 | 0.435 | 0 | 1 |
| | UNI | 4118 | 0.138 | 0.344 | 0 | 1 |
| | GOV | 4118 | 0.096 | 0.295 | 0 | 1 |
| | Spatial reach | | | | | |
| COMP | BE | 4118 | 0.235 | 0.424 | 0 | 1 |
| | EU | 4118 | 0.173 | 0.378 | 0 | 1 |
| | USA | 4118 | 0.046 | 0.209 | 0 | 1 |
| | CI | 4118 | 0.029 | 0.169 | 0 | 1 |
| | OC | 4118 | 0.030 | 0.171 | 0 | 1 |
| UNI | BE | 4118 | 0.126 | 0.332 | 0 | 1 |
| | EU | 4118 | 0.045 | 0.207 | 0 | 1 |
| | USA | 4118 | 0.006 | 0.078 | 0 | 1 |
| | CI | 4118 | 0.003 | 0.056 | 0 | 1 |
| | OC | 4118 | 0.005 | 0.068 | 0 | 1 |
| GOV | BE | 4118 | 0.090 | 0.287 | 0 | 1 |
| | EU | 4118 | 0.028 | 0.166 | 0 | 1 |
| | USA | 4118 | 0.002 | 0.049 | 0 | 1 |
| | CI | 4118 | 0.001 | 0.038 | 0 | 1 |
| | OC | 4118 | 0.001 | 0.038 | 0 | 1 |

**Table 1.3b Descriptive statistics for CIS innovative companies without any patenting activities**

| | CIS companies without any patenting activities | | | | | |
|---|---|---|---|---|---|---|
| | Variable | 1662 | Mean | Std. Dev. | Min | Max |
| | y (productivity) | 1662 | 4.416 | 0.531 | 2.052 | 8.060 |
| | s (size) | 1662 | 3.901 | 1.147 | 1.946 | 10.443 |
| | age | 1662 | 27.782 | 18.853 | 0 | 152 |
| | Types of collaboration ties | | | | | |
| | COMP | 1662 | 0.505 | 0.500 | 0 | 1 |
| | UNI | 1662 | 0.240 | 0.427 | 0 | 1 |
| | GOV | 1662 | 0.164 | 0.370 | 0 | 1 |
| | Spatial reach | | | | | |
| COMP | BE | 1662 | 0.470 | 0.499 | 0 | 1 |
| COMP | EU | 1662 | 0.323 | 0.468 | 0 | 1 |
| COMP | USA | 1662 | 0.073 | 0.261 | 0 | 1 |
| COMP | CI | 1662 | 0.044 | 0.205 | 0 | 1 |
| COMP | OC | 1662 | 0.051 | 0.220 | 0 | 1 |
| UNI | BE | 1662 | 0.221 | 0.415 | 0 | 1 |
| UNI | EU | 1662 | 0.066 | 0.249 | 0 | 1 |
| UNI | USA | 1662 | 0.007 | 0.081 | 0 | 1 |
| UNI | CI | 1662 | 0.002 | 0.049 | 0 | 1 |
| UNI | OC | 1662 | 0.004 | 0.065 | 0 | 1 |
| GOV | BE | 1662 | 0.156 | 0.363 | 0 | 1 |
| GOV | EU | 1662 | 0.038 | 0.191 | 0 | 1 |
| GOV | USA | 1662 | 0.003 | 0.055 | 0 | 1 |
| GOV | CI | 1662 | 0.002 | 0.042 | 0 | 1 |
| GOV | OC | 1662 | 0.002 | 0.042 | 0 | 1 |
| | IMR | 1662 | 0.836 | 0.225 | 0.041 | 1.589 |
| | Breadth | 1662 | 1.463 | 1.845 | 0 | 15 |
| | product | 1662 | 0.678 | 0.467 | 0 | 1 |

**Table 1.3c Descriptive statistics for CIS innovative companies with patenting activity only**

| | CIS companies with patenting activity only | | | | | |
|---|---|---|---|---|---|---|
| | Variable | Obs | Mean | Std. Dev. | Min | Max |
| | y (productivity) | 305 | 4.567 | 0.627 | 0.135 | 7.126 |
| | s (size) | 305 | 4.555 | 1.411 | 2.303 | 9.013 |
| | age | 305 | 33.089 | 23.226 | 2 | 151 |
| | Types of collaboration ties | | | | | |
| | COMP | 305 | 0.279 | 0.449 | 0 | 1 |
| | UNI | 305 | 0.030 | 0.170 | 0 | 1 |
| | GOV | 305 | 0 | 0 | 0 | 0 |
| | Spatial reach | | | | | |
| COMP | BE | 305 | 0.279 | 0.449 | 0 | 1 |
| | EU | 305 | 0.082 | 0.275 | 0 | 1 |
| | USA | 305 | 0.016 | 0.127 | 0 | 1 |
| | CI | 305 | 0.007 | 0.081 | 0 | 1 |
| | OC | 305 | 0.013 | 0.114 | 0 | 1 |
| UNI | BE | 305 | 0.003 | 0.057 | 0 | 1 |
| | EU | 305 | 0 | 0 | 0 | 0 |
| | USA | 305 | 0 | 0 | 0 | 0 |
| | CI | 305 | 0 | 0 | 0 | 0 |
| | OC | 305 | 0 | 0 | 0 | 0 |
| GOV | BE | 305 | 0 | 0 | 0 | 0 |
| | EU | 305 | 0 | 0 | 0 | 0 |
| | USA | 305 | 0 | 0 | 0 | 0 |
| | CI | 305 | 0 | 0 | 0 | 0 |
| | OC | 305 | 0 | 0 | 0 | 0 |
| | IMR | 305 | 0.301 | 0.163 | 0 | 0.844 |
| | Breadth | 305 | 0.400 | 0.705 | 0 | 3 |
| | product | 305 | 0.898 | 0.303 | 0 | 1 |

## Appendix III-2 Robustness check

### Table 2.1 Probit model for IMR

| y=inno | (1) probit | (2) probit |
|---|---|---|
| *Size (s)* | 0.255*** | 0.008 |
| | (0.021) | (0.098) |
| *age2014* | -0.007** | -0.006 |
| | (0.003) | (0.013) |
| *Size_sq* | 0.001 | 1.559** |
| | (0.000736) | (0.636) |
| *age2014_sq* | 52.63 | 69.18 |
| | (35.63) | (135.7) |
| *Industry dummies* | yes | yes |
| *Region dummies* | yes | yes |
| *Pseudo R2* | 0.056 | 0.090 |
| *Prob > F* | 0 | 0 |
| *N* | 3748 | 370 |

(1) includes only those CIS companies which do not indicate any patenting activities
(2) consists only those CIS companies which reveal patenting activity
Notes: * significant at the 10% level of significance; ** significant at the 5% level of significance; *** significant at the 1% level of significance.

where Y is output in terms of innovation, which presented as a dummy variable. This independent variable takes the value of 1 if a company innovates and 0 otherwise.

### Table 2.2 3SLS test

| 3SLS | Model 1 | Model 2 |
|---|---|---|
| *Size (s)* | -0.04 | 0.118*** |
| | (0.067) | -0.041 |
| *age2014* | 0.001 | 0.001 |
| | (0.001) | -0.001 |
| COMP | 0.117*** | 0.232** |
| | (0.026) | -0.099 |
| UNI | 0.112*** | 0.460* |
| | (0.036) | (0.237) |
| GOV | -0.060 | |
| | (0.041) | |
| patenting | | 1.443*** |
| | | (0.524) |
| num_patents | | |
| product | -0.037 | 0.02 |
| | (0.030) | -0.098 |
| IMR | -0.609 | 0.121 |

| 3SLS | Model 1 | Model 2 |
|---|---|---|
| | (0.432) | (0.454) |
| *Industry dummies* | yes | yes |
| *region dummies* | yes | yes |
| *R-squared* | 0.139 | 0.176 |
| *Prob > F* | 0 | 0 |
| *N* | 1662 | 305 |

(1) includes only those CIS companies which do not indicate any patenting activities
(2) consists only those CIS companies which reveal patenting activity
Notes: * significant at the 10% level of significance; ** significant at the 5% level of significance; *** significant at the 1% level of significance.

## Appendix III-3 Tests

### Link test

### Model 1

| Source | SS | df | MS Number of obs= | 1.662 |
|---|---|---|---|---|
| | | | F(2, 1659)= | 124,34 |
| Model | 61,1 | 2 | 30.555 Prob > F= | 0 |
| Residual | 407,7 | 1.659 | .246 R-squared = | 0,130 |
| | | | Adj R-squared = | 0,129 |
| Total | 468,8 | 1.661 | .283 Root MSE = | 0,496 |
| lnproductivity | Coef. | Std. Err. | t P>t [95% Conf.Interval] | |
| _hat | -0,968 | 1,407 | -0.69 0.492 -3.728813 | 1,792 |
| _hatsq | 0,219 | 0,156 | 1.40 0.162 -.0876432 | 0,525 |
| _cons | 4,422 | 3,171 | 1.39 0.163 -1.798151 | 10,643 |

### Model 2

| Source | SS | df | MS Number of obs = | 1.662 |
|---|---|---|---|---|
| | | | F(2, 1659) = | 136,46 |
| Model | 66,2 | 2 | 33.113 Prob > F = | 0 |
| Residual | 402,6 | 1.659 | .243 R-squared = | 0,141 |
| | | | Adj R-squared = | 0,140 |
| Total | 468,8 | 1.661 | .282 Root MSE = | 0,493 |
| lnproductivity | Coef. | Std. Err. | t P>t [95% Conf.Interval] | |
| _hat | -1,526 | 1,355 | -1.13 0.260 -4.184244 | 1,132 |
| _hatsq | 0,281 | 0,151 | 1.87 0.062 -.014405 | 0,577 |
| _cons | 5,661 | 3,046 | 1.86 0.063 -.3134003 | 11,635 |

**Model 3**

| Source | SS | df | MS Number of obs = | 306 |
|---|---|---|---|---|
| | | | F(2, 303) = | 33,64 |
| Model | 21,8 | 2 | 10.882 Prob > F = | 0 |
| Residual | 98,0 | 303 | .323 R-squared = | 0,182 |
| | | | Adj R-squared = | 0,176 |
| Total | 119,7783 | 305 | .393Root MSE = | 0,569 |
| lnproductivity | Coef. | Std. Err. | t P>t [95% Conf.Interval] | |
| _hat | -5,621 | 3,637 | -1.55 0.123 -12.77816 | 1,536 |
| _hatsq | 0,712 | 0,391 | 1.82 0.069 -.0571297 | 1,481 |
| _cons | 15,342 | 8,442 | 1.82 0.070 -1.269373 | 31,954 |

**Model 4**

| Source | SS | df | MS Number of obs = | 305 |
|---|---|---|---|---|
| | | | F(2, 303) = | 34,9 |
| Model | 22,4 | 2 | 11.213 Prob > F = | 0 |
| Residual | 97,4 | 303 | .321 R-squared = | 0,187 |
| | | | Adj R-squared= | 0,182 |
| Total | 119,7783 | 305 | .393 Root MSE = | 0,567 |
| lnproductivity | Coef. | Std. Err. | t P>t [95% Conf.Interval] | |
| _hat | -5,892 | 3,548 | -1.66 0.098 -12.87382 | 1,090 |
| _hatsq | 0,744 | 0,383 | 1.94 0.053 -.0092916 | 1,497 |
| _cons | 15,905 | 8,203 | 1.94 0.053 -.236711 | 32,046 |

**Model 5**

| Source | SS | df | MS Number of obs = | 1.662 |
|---|---|---|---|---|
| | | | F(2, 1659) = | 143,11 |
| Model | 69,0 | 2 | 34.488 Prob > F = | 0 |
| Residual | 399,8 | 1.659 | .241 R-squared = | 0,147 |
| | | | Adj R-squared= | 0,146 |
| Total | 468,7896 | 1.661 | .282 Root MSE= | 0,491 |
| lnproductivity | Coef. | Std. Err. | t P>t [95% Conf.Interval] | |
| _hat | -0,009 | 1,281 | -0.01 0.994 -2.521641 | 2,504 |
| _hatsq | 0,112 | 0,142 | 0.79 0.431 -.1665258 | 0,390 |
| _cons | 2,268 | 2,888 | 0.79 0.432 -3.396877 | 7,933 |

**Model 6**

| Source | SS | df | MS Number of obs = | 305 |
|---|---|---|---|---|
| | | | F(2, 302)= | 36,95 |
| Model | 23,5 | 2 | 11.748 Prob > F= | 0 |
| Residual | 96,0 | 302 | .317 R-squared = | 0,197 |
| | | | Adj R-squared= | 0,191 |
| Total | 119,5 | 304 | .393 Root MSE = | 0,564 |
| lnproductivity | Coef. | Std. Err. | t P>t [95% Conf.Interval] | |
| _hat | -0,588 | 2,205 | -0.27 0.790 -4.926494 | 3,751 |
| _hatsq | 0,166 | 0,230 | 0.72 0.471 -.2869668 | 0,619 |
| _cons | 3,776 | 5,263 | 0.72 0.474 -6.580519 | 14,133 |

**VIF test**

**Model 2**

| Variable | VIF | 1/VIF |
|---|---|---|
| Size (s) | 1,19 | 0,840 |
| age2014 | 1,26 | 0,794 |
| comp | 1,31 | 0,762 |
| uni | 1,72 | 0,580 |
| gov | 1,61 | 0,620 |
| product | 1,13 | 0,884 |

**Model 4**

| Variable | VIF | 1/VIF |
|---|---|---|
| Size (s) | 1,6 | 0,627 |
| age2014 | 1,31 | 0,762 |
| comp | 1,19 | 0,842 |
| uni | 1,14 | 0,877 |
| gov | 1,02 | 0,984 |
| num_patents | 1,27 | 0,788 |
| product | 1,04 | 0,958 |

**Model 5**

| | Variable | VIF | 1/VIF |
|---|---|---|---|
| | Size (s) | 1,23 | 0,811 |
| | age2014 | 1,27 | 0,787 |
| comp | BE | 1,45 | 0,690 |
| | EU | 1,48 | 0,678 |
| | USA | 1,47 | 0,678 |
| | CI | 1,37 | 0,730 |
| | OC | 1,34 | 0,748 |
| uni | BE | 1,9 | 0,527 |
| | EU | 1,77 | 0,565 |
| | USA | 1,61 | 0,621 |
| | CI | 1,97 | 0,507 |
| | OC | 2,06 | 0,484 |
| gov | BE | 1,77 | 0,566 |
| | EU | 1,69 | 0,591 |
| | USA | 2,58 | 0,388 |
| | CI | 3,93 | 0,255 |
| | OC | 2,64 | 0,378 |
| | product | 1,14 | 0,879 |

**Model 6**

| | Variable | VIF | 1/VIF |
|---|---|---|---|
| | Size (s) | 1,65 | 0,606 |
| | age2014 | 1,33 | 0,753 |
| comp | BE | 1,67 | 0,598 |
| | EU | 1,49 | 0,671 |
| | USA | 1,16 | 0,860 |
| | CI | 1,09 | 0,920 |
| | OC | 1,09 | 0,916 |
| uni | BE | 1,08 | 0,925 |
| | num_patents | 1,28 | 0,780 |
| | product | 1,05 | 0,952 |

## Appendix III-4 Additional data analysis

Additional data analysis has been empirically tested in this work. We applied the same research questions to the CIS and Patstat databases which include both innovative and non-innovative companies. The results indicate similar trends as have been observed in the datasets which included only innovative companies. Additionally, we have analysed the dataset which included only non-innovative companies. The results reveal no impact on productivity performance.

CHAPTER VI

# CONCLUSION

## 6.1 Main lessons of the research

R&D activities are unequally divided across space (Aydalot, 1985; Kleinknecht and Poot, 1992). To understand the reasons behind this unequal spread, we are interested in factors determining the location of R&D. The concept of regional innovation systems has evolved into an accepted way of understanding the uneven spatial development of the knowledge economy. The concept is explicit that both knowledge producers and exploiters are active in their own global networks, but competitive advantage is produced regionally through interactions which create supporting institutions. The role for regional innovation policy is to support exchange between those actors and to create new pathways for exchange—new innovation instruments such as innovation vouchers, industry fellowships, or industrial chairs. This approach of regional innovation systems is highly influential in European innovation policy which is at the centre of European structural policy (Benneworth et al., 2007).

The research developed in the previous chapters aims to contribute to the existing literature and assess the impact of the location of R&D on firms' performance. The literature review in each chapter identified several less explored areas in the field of R&D performance and spatial development, and the present Ph.D. thesis intends to fill these gaps.

**Chapter II** complements existing information about the Brussels regional innovation system with additional data that are less frequently available through current channels or difficult to make public due to the number of data manipulations. In this part of the research, we illustrate the Brussels Innovation System by focusing on various aspects related to intra- and interregional connections. The dataset is based on scientific publications and patents over the period 1993-2013 containing at least one author with an affiliation or inventor located in the Brussels-Capital Region, Vienna and Berlin. The main objective of this Chapter is to compare Brussels with Belgian regions, city agglomerations and districts, as well as with capital cities of metropolitan regions (Vienna and Berlin) in terms of patenting and producing scientific publications, in order to map and understand how knowledge exchange takes place when Brussels actors are involved and which partners, locations, scientific fields and technological sectors are preferred. We construct indicators based on patents and scientific publications and provide guidelines for the compilation and interpretation of these indicators.

Patent data highlight the position and specialisation of regions, districts and countries across areas and different fields in our study. Overall, the Brussels-Capital Region tends to patent relatively more than other Belgian regions, city agglomerations or districts since the analysis is based on patents with inventors located in Brussels. With regard to the analysis made between comparable capital cities of metropolitan regions, in terms of patent applications Brussels performs more efficiently than Berlin and Vienna.

There is also evidence that Companies and Individuals tend to patent more than Universities and Government non-profit organisations at all spatial levels. One potential explanation is that the high cost of the patent application procedure might cause Universities and Government non-profit organisations to choose not to patent or patent less. The other issue is that due to the delay in patent filing and academic publications, there is reduced diffusion, etc. Based on these facts, the government might consider a series of policy measures aimed at fostering the diffusion of university research. In addition, changes in patent regimes might contribute to an increase by making patents more valuable and easier or less costly to obtain. Stimulating Universities will increase the number of patent applications.

Another important finding of our research indicates that the ICT and Environment sectors are less present than other sectors (for example, Health and Medicine) in regions and city agglomerations. The comparison between metropolitan regions showed significant growth in the ICT sector, but this sector shows the lowest performance. Most patent offices have seen a surge in patent applications in the past two decades, with the largest contribution to growth being made by ICT. The expansion of ICT, which is reducing communication costs, may increase the number of forms of collaboration, from sponsored and collaborative research to strategic alliances, mergers and acquisitions, and technology licensing.

As patents play an essential role in market-centred systems of innovation, economic criteria should be used more systematically to evaluate patent systems' ability to foster innovation and to encourage technology diffusion and knowledge flows.

Scopus indicators reflect scientific output, as measured by journal counts. The basic indicators of scientific publications still have a long way to go, providing an essentially objective quantitative measure of scientific output. Each indicator has its advantages and limitations. The various procedures and methods need to be used in combination for scientific publication indicators, despite the contradictory results, as long as they offer useful information and comply with scientific and professional standards.

Belgium in general has strong research universities as reflected in the number and quality of scientific publications. Publication growth has been mainly concentrated in higher education institutions, reflecting the increasing share of higher education R&D expenditure at all spatial levels. Policy implications should continue to nurture high quality research performed in the public sector. This involves maintaining healthy funding streams for research. Additionally, better exploitation of the results of this research in commercial terms could be achieved by fostering S&T collaboration between public research institutes and private companies. Further stimulation of funds from industries will promote more collaboration with Universities and Government-non-profit organisations. Concerning the coherence between the scientific and technological fields of specialisation in the Brussels-Capital Region, another recommendation may be to develop clusters and smart specialisations.

In **Chapter III** our research is focused on the different spatial levels which can be accounted as factors influencing on productivity growth of R&D active firms. R&D performance may significantly vary between different spatial levels. For this reason, R&D activities considered as an appropriate tool to analyse regional economic development and growth. The topic of the spatial pattern in R&D activities was investigated by list of scholars. It is worthwhile to explore the dynamism and change of R&D activities' spatial spread as R&D activities are very much a dynamic phenomenon and the consequences in terms of past growth of these activities have painted the current relative position of the regions. The main aim of this Chapter is to foster attention on productivity growth of R&D active firms at the smaller spatial levels (provinces, districts, city agglomerations). Besides, the research extends the existing literature in several ways: analysis of a lower spatial levels such as provinces, districts and city agglomerations in order provide a clearer view on a more detailed country profile of Belgium and it's spatial disparities; comparison of obtained results with previous investigations about Belgium and its spatial differences; assessment of the output growth regarding to the different spatial dimensions.

Based on the Cobb-Douglas production function and panel data, the results from the estimation of the baseline equation show a positive and significant impact of R&D stock on output growth, with a rate of return 4%. These results are in line with the literature. Further investigations in terms of regional differences indicate slight variations of R&D rate of returns between regions which can be explained by a catching up process associated with a smaller technical gap between regions compared to ten years ago.

In terms of provincial level, the empirical results point to the presence of provincial disparities in Belgium. The rate of return to R&D stock varies among Belgian provinces for the period 2000-2013. The Brussels province reaches the highest rate of return to R&D stock (nearly 4.3%) whilst Antwerp, Flemish Brabant, Walloon Brabant, West Flanders and East Flanders provinces show rather similar R&D elasticities. Such trends can be explained by industrial specialisation of the provinces, such companies like BASF, Agfa Gevaert, Borealis and Solvay mainly located in the area around.

The performance in terms of district agglomeration level points to a significant impact on output growth in 32 districts, however, 11 districts do not show any significant results. Positive and significant effect of output growth indicates such districts as Aalst, Ghent, Saint-Nicolas and Dendermonde which belongs to the East Flanders province. The West Flanders province also reveals some districts with positive and significant effect in the growth of value added: Bruge, Kortrijk and Ipres. Considering the Antwerp province, we identified few districts with significant influence on output growth such as Antwerpen, Mechelen and Turnhout districts. The other group with meaningful outcome presented by the Flemish Brabant and Liege provinces which include Halle-Vilvoorde, Leuven districts and Liege and Verviers districts. The highly significant positive values of the respective coefficients indicate that neighbouring districts share some common influences.

Finally, we investigated the measurement of the returns to R&D on output growth by city agglomeration level. The elasticities of R&D stock for the Brussels city agglomeration indicates towards a positive and significant influence on output in terms of value added growth. The Large city agglomerations reach higher rate of return to R&D stock (4.2%), while the Regional city agglomeration indicates lower rate of return to R&D stock (2.4%). The rate of return to R&D stock in the Brussels city agglomeration does not differ much from those in the Brussels-Capital Region. The results at the level of the Brussels-Capital Region are largely confirmed at city agglomeration level. However, the results in our study do not indicate distinctions between the Brussels-Capital region and the Brussels city agglomeration. The findings of Teirlinck and Spithoven (2018) at the Brussels-Capital Region and at Brussels city agglomeration level confirm that particularities of Brussels are not restricted to the Capital Region but can be seen at an overarching Brussels city agglomeration innovation system. The stimulation of R&D growth will diminish spatial differences.

In the next **Chapter IV**, we examined the performance in terms of output growth of research active companies with spatially diversified patent collaboration networks. Although the literature on the relations between patents and output growth of R&D active companies has been widely investigated, there has been little research with respect to the impact of patent collaboration networks on the output growth of R&D active companies. The research responded to the following gaps in the literature: (i) analysis of different patterns of patent collaboration networks involving companies and individuals, thus adding to the debate on boundary spanning in regional innovation systems; and (ii) use of original data on patent collaborations in research active companies with attention to knowledge distribution between companies and individuals; and (iii) implementation of a novel approach by including the spatial reach of patent collaboration networks. The main contribution of this chapter is not merely to replicate measurement of the returns to R&D, but to supplement it by including the spatial reach of patent collaboration networks and its impact on firms' output growth.

Several facts about co-applied patents are found. 14.6 % of all patent applications are the result of co-application relations which is indicating a growth trend in the number of co-applied patents in recent decades. Additionally, we distinguish about 50 different types of patent co-application ties between different organisations. The highest share of co-applied patents involves mainly between companies and individuals (63.2%), over 20% of individuals co-apply with other individuals, and 5.2% domestic companies co-apply with foreign companies on patents. Hence, the main focus in this chapter rests on company-individual co-application relationships.

Results from the estimation of the baseline equation show a positive and significant impact of R&D stock on output growth, with a rate of return 4%. Further investigations in terms of regional differences indicate slight variations of R&D rate of returns between regions.

Based on the analysis of the impact of patenting activities of R&D companies within the company-individual co-application ties on output growth, the results suggest that co-applied patents of the firms positively influence output growth. Additionally, we observed substantial different effects of patenting activity on output growth in one region, where the Flemish Region is characterized by a positive and significant effect of patenting activity on companies' output growth and the Brussels-Capital and the Walloon Region exhibit a weaker performance. Such trends can be explained by the industrial specialisation pattern, technical performance of the regions as well as the research orientation of companies in the regions.

Chapter IV also investigated the behaviour of R&D active companies regarding patent collaboration networks between inventors in company-individual co-application ties. Results suggest that knowledge flows through patent collaboration networks, involving an R&D active company and individuals, yield a positive and significant effect on the company's output growth. Further analysis also highlighted the existence of regional differences.

As a final point, we investigated the impact of the spatial reach of the patent collaboration networks involving company-individual ties on output growth. Significant impact on output growth is observed when the patent involves a collaboration with at least one inventor from the rest of the world; and with at least one inventor from the EU. The collaborations among individuals with at least one inventor from the rest of the world (ROW) is the network contributing the most, followed by patent collaboration networks involving at least one individual from the EU (EU). Technical innovations involving inventors in the rest of the world complements the knowledge in Belgium and leads to a positive impact on output growth. Regarding the regional differences, a spatial reach with involvement of inventors from the rest of the world and the EU benefits output growth in the Flemish Region and the Walloon region, whereas a spatial reach with involvement only Belgian inventors exclusively benefits output growth in the Brussels-Capital Region.

For the period 2000-2013, the results indicate a positive and significant impact on the company's output growth when R&D active companies are involved in a patent activity with individuals. However, the most influential R&D companies with company-individual co-application relations in terms of output growth are those ones which involve international collaboration networks. These findings suggest that further motivation and implication of R&D companies to enter into co-applied agreements with foreign inventors (individuals) may positively increase the output growth of a firm. As emphasized by Kumar and Margun (1998), joint innovation activities have a tendency to lower the costs for developing new technologies, as well as eliminating the effort of producing duplicated research, allow collaborators to share the risk related to R&D and help to get a faster access to other necessary sources in order to finalize such complex projects. Due to the country size, Belgium is not able to have sufficient resources to cover all range of technological fields in comparison with large countries. Hence, the expansion of bi-lateral science and technology agreements with other countries can positively influence and as well encourage R&D companies to be engaged into co-application patenting processes. However, intra-regional collaborations are more important than inter-regional ones due to the evidence of a spreading-out process of regional innovation systems (Capron and Cincera 1999). The results obtained for the Belgian regions in our chapter indicate a marked contrast between regions. The policy focus should be put to stimulate the diffusion of knowledge, S&T policy at regional level, in order to improve intra-regional collaborations. The emphasis of collaboration networks in turn will increase regional competitiveness.

**Chapter V** offers additional evidence to confirm the prevalent assumption that collaboration ties can influence performance. Scholars in the innovation and inter-organisational learning works have reasoned that linkages and the collaboration networks provide the access to external knowledge (Powell et al, 1996). The limited empirical evidence on characteristics of collaboration ties that influence performance has prevented researchers from understanding which collaboration ties contribute most to company productivity performance and in general how companies can best use collaborations as part of their knowledge creation strategies. Although prior work has shown that collaborations do matter for company performance (e.g., Ahuja, 2000).

The analyses conducted in this study confirm the hypotheses outlined: H1a: Innovative companies that have a larger variety of inter-organisational collaborative types of partners have a higher productivity performance; H1b: Inventive companies that have a large variety of inter-organisational collaborative types of partners have a higher productivity performance, but not different from innovative companies without patents.

The different collaboration ties measured by CIS and Patent databases enhance the performance of the Belgian innovative companies. We analysed this issue with inter-organisational collaboration data from CIS and patent data from Patstat covering 2014. The effects of collaboration network position on performance are clear and beneficial. These findings confirm that collaborative ties are the opportunities for learning and innovation. Controlling for other explanations, age has not indicated the impact in our analysis. Similar results were found by Powel et al. (1996) where the authors explain this fact as companies do not avoid collaborations as they grow older, and the size has no predictive influence on productivity.

The most interesting ancillary finding is that the collaboration ties between companies are the most contributing followed by collaboration ties involving universities and government, public or private research institutes. The dataset which consists only those CIS innovative companies with patenting activity indicated similar outcome for the collaboration ties between companies and followed by universities. However, some limitations have been encountered, the collaboration ties with government, public or private research institutes were not found in patent sample with CIS innovative companies, which in turn prevented our analysis to make a comparison with CIS database where companies are not involved in patent activities.

This study's findings suggest that companies should consider the idea of inter-organisational arrangements in order to be effective in terms of productivity performance. It was observed during this study that inter-organisational collaboration with different partners (with other companies, universities and government, public or private research institutes) contributes to the productivity performance of companies, while, at the same time, the observed relationships differ from each other and indicate the different impact level on productivity performance. These results highlight the relevance for senior management of adopting an approach to inter-organisational collaborations, involving innovations and patenting activities, in order to achieve higher results in terms of developing existing technologies and creating new ones. Such inter-organisational ties might result in the creation and development of resources (Das and Teng, 2000), might help to spread the costs of research and development (Veugelers, 1998; Hagedoorn, 2002), and at the same time reduce the risks associated with innovations.

Another implication of this study that merits emphasis is the analysis of inter-organisational networks and their spatial reach which enlarge our understanding of collaboration ties. The secondary spatial dimension in terms of the spatial reach is presented through Belgium, EU, USA, China/India and other countries. The following is hypothesized:

**H2a:** The spatial reach of innovative companies that engage in a variety of inter-organisational collaborative types of partners have a higher impact on productivity performance.

**H2b:** The spatial reach of inventive companies that engage in a variety of inter-organisational collaborative types of partners have a higher impact on productivity performance, but not different from innovative companies without patents.

Collaborations between companies at different spatial levels have a relatively significant impact on productivity only in case when international spatial reach is involved both in terms of innovations and patent collaborations, where the CIS sample emphasis more international impact through EU and other countries and Patstat sample in turn highlights the importance of USA based international spatial reach. The collaboration ties with universities have a stronger impact on the productivity performance when the Belgian and other EU countries' spatial reach is involved. Additionally, the results show that the international (non-EU) collaborations do not have any impact. Collaboration between companies and government, public or private research institutes does not show any significant impact at any spatial reach level on productivity performance of the companies. The outlined hypothesises were partially confirmed in this part of the analysis.

To sum up, R&D has to be considered as the necessary first phase of any process leading to technological innovation. R&D embodies a long-term vision of an organisation and its strategy when innovation operates more in a short-term economic model of the organisation. The experience and the knowledge accumulated thanks to R&D activities enhance innovation (Brouwer et Kleinknecht, 1996). The research focused on R&D and innovations can be considered as an essential first step if an organisation wants to be innovative.

Even though in this thesis the outdated data was used, nevertheless, it contains critical information about the way entities or systems have changed with time. When certain properties of the outliers are only revealed infrequently, outdated data may be the best, sometimes the only, sources of information about those critical values from the norm. The data on R&D and innovations are highly important and one can use them for shedding light on various topics of interest.

Regarding the results of the empirical analyses revealed that detailed knowledge of the different spatial categories situation is a necessary precondition for designing adequate policy measures to meet the individual needs of regional economies and spatial interdependencies. Therefore territorial cohesion should be an issue of policy at the national or regional level and not a task of EU policy.

Research on R&D partnerships in this thesis repeatedly highlights the dignity of collaborative innovation. In general, collaboration relations are fundamental to bridge the boundaries within the NIS and to let the various actors share their skills, knowledge, capabilities and expertise in order to facilitate innovation and drive competitiveness. The ultimate aim of policy intervention is to bring about change in practices. Collaborations can be stimulated through various strategies (change of management system, funding incentives). It should also be taken into account that collaboration can bring risks – and these are factors that must also be considered in the design and formulation of support policies and when considering whether a policy intervention should be developed at all.

In my opinion, this research can bring additional insights into aforementioned intercorrelated topics that can unlock new opportunities for further investigation.

## 6.2 Main limitations of the research

The main limitations of the studies are linked to data characteristics. For **Chapter II**, where PATSTAT and Scopus database are used, the main issue is the nature of these databases. The PATSTAT raw data has some problems in terms of spelling mistakes in the city names which makes the search process more complicated and requires more time to clean and harmonize data. The main issue we faced was identifying regions/city agglomerations/districts from names of smaller cities, this information requiring much manual search. The PATSTAT data for Brussels was cleaned according to the city and country's names, with few unrecognizable observations appearing in the sample. The PATSTAT data for Vienna required some attention due to spelling problems and written mistakes in the country names. The PATSTAT data for Berlin required the same attention as the Austrian data.

The main issue of Scopus data concerns spelling mistakes (using different languages, abbreviations, written mistakes), which makes the process of identifying cities and organisations slow and unclear. For example, nearly 5 % of countries were not detected due to spelling mistakes or completely missing data. 4 % of cities were not identified and assigned to the district or region level. In the following step of identifying universities, organisations, companies and institutions, 25% of observations were not recognised. The cleaning process of data for Vienna was more time-consuming as we found many spelling mistakes or missing values. To reduce this problem, we developed an additional search with countries and names of different organisations. We were not able to detect 83,008 observations out of 250,409. Using specific manipulations, we reduce the number of unidentified observations to 72,466, which is 28.9%. We also faced similar difficulties in cleaning the Scopus data for Berlin. As we found many unidentified observations in the raw database, we implemented similar methods to solve the same issue. At first, we could not identify 124,936 observations out of 405,823. After the cleaning procedure, we reduced this number to 93,457 observations, which is 23%.

Similar issues were detected during patent data processing in **Chapter IV and V**, where CIS and bi-annual R&D survey databases are matched with the patent data using the names of the companies as a common identifier. The names of the same organisations can have different spellings which make matching process inaccurate. The companies' names were identified and corrected through manual cleaning. Special attention was given to the universities, because 'KULeuven' and 'UCL' are sometimes incorrectly identified due to the use of the same (English) name. Also, the identification of the type of organisation is not always correct in the original patent dataset.

In **Chapter III and IV** the primary data source is drawn from the Belgian biannual R&D surveys, jointly organised by the Belgian Federal Science Policy Office (BELSPO). These longitudinal unbalanced dataset record of a representative sample of R&D performing companies in Belgium over the period 2000–2013 and contains 7,652 companies. Due to the fact that this information comes from a survey and that the companies were not compelled to answer, the database is strongly unbalanced. To render the database balanced and applicable for construction other variables such as R&D stock, we consider only companies which have R&D expenditure data for five subsequent years. All companies which do not have R&D data for at least five subsequent years are removed. Nevertheless, in this approach a new limitation emerged, the reduction of the sample size. As a result, we have a database of 3,686 companies, where we checked for the representativeness of the database.

As regards data limitation in **Chapter V,** the main restriction of the study could be the nature of the Community Innovation Survey database. As mentioned by Teirlinck and Spithoven (2008), the survey captures an aggregated innovation behaviour of firms. The analysis, due to response problem, does not take into account mutually exclusive activities for external knowledge relations (such as sources of innovation, collaboration on innovation). Additionally, measuring within the same (two-year) timespan the interactions between the degree of openness of innovation and external knowledge relations and the type and degree of novelty of the innovation is problematic.

In **Chapter III**, one additional limitation could be the issue of spatial autocorrelation. The empirical analysis of this Chapter involves the data which contains the location of observations. This data can embed some spatial pattern which might cause a number of measurement problems, known as spatial autocorrelation effects. The spatial autocorrelation appears as observation in spatial proximity is matched by value similarity (Anselin, 1995). For the issue of spatial autocorrelation sophisticated body of specialied techniques have been developed (Griffith, 2013; Halleck & Elhorst, 2015). However, the common issue arises from the quality of data source and its availability at the micro level which is not very common in Europe as in US. As a result, none of the methods can be applicable to our data base due to large amount of missing values, which causes the main issue in generating a matrix of weights based on the locations. However, we conduct additional test designed primarily to ensure the robustness of the sign and significance pattern of the empirical model proposed in Chapter III.

Finally, another limitation in **Chapter V** was the collaboration ties with government, public or private research institutes were not found in patent sample with CIS innovative companies, which in turn prevented our analysis to make a comparison with CIS database where companies are not involved in patent activities.

## 6.3 Further research

Taking into account the data collected in this Ph.D. thesis for Chapters IV and V, as well as the findings highlighted, further research should explore the following aspects.

A problem that is appearing in this research is the lack of an indicator of the scale or number of collaborative innovative activities of each type in the European Community Innovation survey data used here. To examine accurately the impact of innovative inter-organisational collaborations on productivity performance for Belgian companies, information on the number and importance of such ties may be crucial. Here an alternative approach would be to utilise databases on innovative inter-organisational collaborations that have been the subject of analysis in most of the management literature. Moreover, the dynamic evaluation might present a more comprehensive picture of the collaboration ties performance. Further studies could conduct a comparative analysis to account for the effect. Meanwhile, including sectoral analysis with the updated and elaborated dataset can bring additional insights to the research.

In addition, the mix of collaboration ties and their contribution to the productivity performance must be investigated further. The future research could contribute by examining how particular inter-organisational ties have an effect in longer term. Future studies could utilize more recent years, to confirm the results. The possible expansion of the database can also allow to analysis and compare in detail the spatial reach of the collaborations ties which involve government, public or private research institutes.

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