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OPENNESS AND INNOVATION PERFORMANCE IN REGIONAL INNOVATION SYSTEMS

PhD THESIS BY HEIKO UNZALU TROYA

Director: Mario Davide Parrilli

Co-Director: Susana Franco Rodríguez

“Wer den Dichter will verstehen
muss in Dichters Lande gehen”

—Goethe

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CHAPTER 1

INTRODUCTION

1. Introduction

1.1. Context and Rationale

This thesis deals with the role and effects of openness on the performance of innovation in regions. In this study, openness is understood as social and economic openness through inclusive labour markets and movements of goods, capital and people. The greater the flow of goods, capital and people, and the greater the participation of all groups from society in the labour market, the more open will the region be considered.

The concept of regional innovation systems has received a lot of attention from policy makers and academics in the field ever since its publication by Cooke (Cooke, 1992). Moreover, a large part of the European Union (EU) investments through the EU structural funds are targeted to creating regional innovation systems. This is because region is considered to be the appropriate geographic level to implement innovation policies. On the other hand, the main argument from advocates of national innovation systems (B.-A. Lundvall, 2007) is that education systems, labour markets, financial markets, intellectual property rights, competition and welfare regimes, all have a great influence on innovation systems and have been traditionally set up at national level.

Nevertheless, and especially in the European Union, these policies are increasingly set up and harmonised at supranational (EU) level. This increases the influence of the RIS literature and warrants that policies be implemented not only by taking into account the central role of regional institutions but also the interaction of firms, universities and R&D labs at that level.

Furthermore, economic development leads to an increase in the knowledge intensity of products and services, which in turn leads to geographic concentration of economic activity. This is a result of the complementary condition of codified and tacit knowledge due to the limited geographic transferability of the latter.

A Regional Innovation System materialises when a systematic interactive learning process takes place between the knowledge generation subsystem (university, research labs, etc.), the knowledge exploitation subsystem (firms) and the autonomous regional and financial public institutions (Cooke, 2001). The relationship between openness, innovation capacity and regionalisation is still valid today, despite the same also being present in the fundamental disruptive changes that have taken place in the world economy ever since the industrial revolution (Dobbs, Manyika, & Woetzel, 2015). The main pillars of the innovation trend are 1) urbanisation, 2) the accelerated pace of technology change, 3) an ageing population, and 4) greater global connections in trade, people, finance and data. These factors interact and feed upon one another and together produce a great influence on the world economy.

The trend towards urbanisation is closely related to Cooke's observation of regionalisation of the innovation system. Regionalisation and innovation are the result of an increasing regionalisation and concentration of the economy. It has been observed that the more knowledge intensive the economic activities, the greater their concentration in a few locations around the world (Maskell, 1999). Therefore, the trend to urbanisation is closely related to the second disruptive trend in the world economy, i.e., the accelerated pace of technology change. Nokia's underestimation of the smart phone trend terminated the company's mobile phone business (which in 2007 seemed to be a perfectly healthy conglomerate with tens of thousands of employees employed in this mobile phone business sector) in 2015. Examples like this illustrate how fast technology changes today.

Moreover, new technologies such as smart phones provide the means for instant sharing and communication, thus contributing to the fourth disruptive change: the free flow of data is in the hands of everyone with more than half of the world population with a mobile phone connection and access to Internet (GSMA-

Intelligence, 10.08.2015). Large high-tech corporations such as Alphabet (Google) and Facebook are currently connecting those who do not have an Internet connection in the third world with flying drones (S. Schmitt, 06.08.2015).

The third fundamental trend is the ageing population in many parts of the world. The issue of the aging population increases dramatically in some countries of Europe such as in Germany. This is also linked with the fourth disruptive change, i.e., the increasing global connection in trade, people, finance and data. Much has been said about globalisation and the increasing international integration of finance, economies and culture, which are a consequence of major achievements in the transport and telecommunications sector. Production systems are today organised within global value chains (GVC) and global production networks (GPN), which have become the backbone of world economy (Neilson, Pritchard, & Yeung, 2014). Simultaneously, migrants fill the void left by the increasing retirement rates due to the aging population in Europe. Trade and data flows furthermore put an unprecedented level of information and codified knowledge in regions unknown to decision-makers a few decades earlier.

The study on migration flows towards regions is one of the cornerstones of this thesis. An open region is one that is able to attract people from other parts of the world. Migration flows into Europe are more up to date than ever for two reasons. On the one hand, migrations from outside the European Union have increased considerably in the last years. According to the latest public opinion poll of the European Union published in July 2015, immigration is now seen as the most important issue facing the EU (Eurobarometer, 2015), ahead of economic stagnation and unemployment. The second reason is the flaws that persist in the Eurozone. Migrations will essentially be encouraged within the Eurozone in the coming years, for instance through a uniform social security scheme. This would make the area more flexible to asymmetrical economic shocks (Mundell, 1961).

It is easier today for a person from Alabama to go to work in Massachusetts than for a Portuguese citizen to go to work in France. Nevertheless, there could be positive effects derived from the rich cultural and linguistic resources in the Eurozone. In fact, the United States is the best proof that a multiracial, multicultural and multi-religious society can exist, develop and progress at a remarkable rate, creating opportunities that attract people from around the globe. If the Europeans were to put all nations in a so-called melting pot, then Europe too could take advantage of its varied and heterogeneous linguistic and cultural resources. The idea that diversity may be beneficial is ultimately based on an intuitive thinking derived from Darwin's evolutionary theory. Research has shown that the more different the parents, the higher and more intelligent their children will be (Joshi, et al., 2015). Meaning, genetic diversity is rewarded with height and intelligence.

In the context of this thesis, the inclusiveness of the labour market is a sign of openness. Accordingly, the greater the female participation and that of youth and minorities, the more open will the labour market be. Acemoglu and Robinson (2012) studied the reasons for the prosperity and fall of the nations in "inclusive economic institutions" (which widely distribute political and economic power within an inclusive market economy). Putting it in Obama's words, during the first visit ever of an American president in Kenya: "If half of your team is not playing, you've got a problem", referring to women excluded from the formal economy (CBCNews, 2015). An open society shows an inclusive labour market where women, young people, and minorities are not marginalised. Marginalisation of groups exists not only in Africa but also in large parts of the European Union. Its detrimental effect on the economy needs to be understood and communicated as a means to increasing acceptance towards a tolerant society. People need to be made aware that intolerance is costly and affects their income directly.

An open economy permits the free flow of trade, services and capital, and people beyond its borders. The degree of openness is measured in terms of the capacity of trade, services, capital and people for transferring tacit knowledge into the region. Tacit knowledge as opposed to explicit or codified knowledge is knowledge that cannot be easily verbalised and written down, since it is knowledge that a person is not explicitly aware of based on the idea that a person "knows more than he can tell" [(Polanyi, 1967): 4]. Consequently, tacit knowledge is transferred by working together from master to apprentice, in working groups, through socialisation, but cannot be transferred through distance. Therefore, openness of the economy is analysed not only from the perspective of inward flows of people and inclusiveness of the economy but also inward flows of capital in the form of FDI, foreign ownership of domestic inventions, foreign human resources in the science and technology system, and foreign students in tertiary education.

These indicators bring new tacit knowledge into the territory since they imply people travelling and participating in the working and social life of the region. FDI and foreign ownership of domestic inventions bring tacit knowledge in the form of new management methods into the country. Immigrants do not only bring tacit knowledge in the form of skills but also as a broader tacit knowledge that enriches the region's social capital. Enfolded communities help to bridge their tacit knowledge through socialisation, externalisation, combination, and internalisation (Nonaka & Takeuchi, 1994; Williams, 2009). Trade on the other hand is more related to the exchange of explicit knowledge since it does not necessarily involve people working physically together.

Openness permits the flow of tacit knowledge, which is complementary to codified knowledge, i.e. written knowledge, information and data that are available and remotely accessible through information and communication technology (ICT). Codified knowledge written down in codes and signs can be sent and received instantly. What cannot be received is the underlying learning process or the complementary tacit knowledge (Foray & Lundvall, 1998). This is exchanged through persons by working together in close proximity. The understanding of openness here therefore differs from the classical definition of openness in the economy, which is traditionally based on ratios of exports and imports on GDP. This thesis is based on the differentiation in flows of codified and tacit knowledge. It is the same differentiation on which the Regional Innovation System literature is based (Lawson & Lorenz, 1999).

The literature on openness for regional innovation is rather limited. The concept of 'openness' has been mainly applied to trade policy and its effect on economic growth. Harrison (1996) performs a set of causality tests and finds evidence that greater openness is associated with higher growth, although both relationships, i.e. higher openness that leads to higher growth and vice versa, can be found in the literature. Simultaneously, in the context of countries, Edwards (1998) found evidence that more open trade regimes lead to higher growth of productivity.

Laursen and Salter (2006) discuss the role of openness for innovations in firms in the United Kingdom. Openness is applied here as external search strategies, in terms of external search breadth and external search depth, which describes the character of the firm's strategies in accessing knowledge sources outside the firm. They found that firms that develop broad and deep search strategies are more likely to have a higher innovative performance. Chesbrough (2003) analyzed the concept of open innovation strategies in firms, and found similar results. These authors consider openness as a complement to internal R&D efforts in the firms.

The first comprehensive literature review of openness in terms of internationalization is performed by Carlsson (Carlsson, 2006) who connected it with the development of innovation systems. In general, the majority of the literature in this area relates globalization with international trade and foreign direct investment, since activities that deal with R&D are the less internationalized of all activities. Niosi and Bellon (1994) analyzed the degree of internationalization of innovation systems in the United States, Japan and leading countries in Europe and concluded that the R&D of multinational firms, international technical alliances, international technology transfers and international mobility schemes of science and technology personnel are higher in smaller countries. Larger countries tend to be more self-sufficient. In addition, collaboration in patenting seemed to enjoy the highest degree of globalization among all R&D operations.

The first author that discussed the role of openness not only in terms of human capital but also in terms of the creative class was Florida (2002a). He found that cultural amenities measured by the "Bohemian index" are highly correlated with both human capital and high technology. This stream of literature finds that diversity and openness in terms of tolerance can benefit regions in attracting talent and economic investments. While there is no consensus on the role of industrial diversification (diversity vs. specialization), the literature acknowledges the role of demographic and social diversity in terms of age, race, nationality or sexual orientation for innovation (Saxenian, 2002b). In this stream of literature, openness is applied as the ability of regions to attract talent from various ethnic backgrounds, which are argued to have a positive impact on the stock of human capital (Florida, 2007).

The regional innovation systems literature relates openness with human capital and its flow across countries (Bathelt, Malmberg, & Maskell, 2004). Simultaneously, Florida studied openness in relation with human capital and the creative class, and applied it to the city context. What remains unknown is the complementary role of knowledge and openness in regional innovation systems. Both concepts bring together codified and tacit knowledge into the region that have a positive effect on creativity and innovations in the innovation system. While all studies on internationalization and openness acknowledge an increase of international activities with regards to innovation, all literature state that national and increasingly regional innovation systems become more essential as a result of tacit knowledge exchanges (Bathelt, et al., 2004).

In our work, the dimension of 'openness' is applied to national and regional innovation systems and their human capital and creative class, building upon the literature of Florida (Florida, 2002a). Openness is regarded as a key instrument to transport codified and tacit knowledge into the region. All people carry a tacit knowledge that has been built up throughout their life. Therefore, no distinction is made on the actual stock of human capital of the individuals. All migrants carry knowledge with them (Williams, 2007a). Therefore, while many relationships are still unknown, the concepts used in this thesis apply to the regional innovation systems literature in relation to the complementary role of codified and tacit knowledge (Lundvall, Johnson, & Lorenz, 2002), the role of the creative class in the cities (Florida, 2002a), and the interplay of internationalization and regional innovation systems (Bathelt, et al., 2004). It is still unknown whether openness has a positive effect in regions with high capital stock or not and the possible reasons for it.

Given that access to information and codified knowledge are more easily transferable, they also tend to be non-rivalrous (2002). Intellectual property rights might protect the codified knowledge of the inventor but do so for only a limited period of time. Furthermore, not all ideas are patentable, not all industries patent in the same way, and public research in a region is a public good worldwide (Stiglitz, 1999). On the other hand, tacit knowledge is rivalrous because agents can easily exclude others from it. This is the main force that leads towards an increasing regionalisation of the knowledge-based economy. Therefore, the definition of openness is centred on the ability to integrate tacit knowledge in a region.

Policy makers will be able to develop a specific regional strategy for economic development, if we can contribute to the understanding of the mechanisms that would ultimately lead to convince for the need for an inclusive economy, migrants, and inward foreign direct investment, among others.

Moreover, a theoretical understanding would also help managers in large multinational companies to understand the benefits of openness (i.e. innovations and creativity) for firms. For instance, there is a debate on opening the administrative boards of companies to female managers (Nielsen & Huse, 2010). However, this debate goes much further than that. The essential argument here is whether it is optimal, in terms of creativeness and innovativeness, for companies such as Volkswagen AG, that generate huge profits all around the world, to have a board that is purely male, German and between 50-60 years old? The strategy consultancy firm Roland Berger opines that companies can benefit by entering new product niches and markets and attract best talents through diversity and inclusion policies (Berger, 2012). German companies alone could save up to 21 Billion Euros through the introduction of diversity and inclusion management systems. For instance, Jeremy Tai Abbett , Google manager in charge of creativity, considers team diversity with respect to experience, gender, age, points of view, etc. as a fundamental source for creativity and innovation capacity in companies (Abbett, 2015).

1.2. Objective

The aim of this thesis is to find out whether the more open regions are more creative and innovative. Does openness need to be developed together with other innovation ingredients? And should codified knowledge (increased among others through R&D investment) be developed along with complementary tacit knowledge? How can one understand the role of openness and are there other instruments that promote access to the tacit knowledge pools? How should we understand the interplay between codified and tacit knowledge?

A model was built to provide answers to these questions. Economic prosperity rests upon knowledge and its useful application (Teece, 1998), which is innovation. Innovation is defined as the intentional introduction and application within a role, group or organisation, of ideas, processes or procedures that are new and beneficial to the group (West & Farr, 1990). Technological, strategic and market related knowledge is needed to enable innovation. Innovation is an inter-individual social process (Anderson & King, 1993).

Therefore, the starting point of our model is that knowledge collaboration with the external world is required as a means to innovate. Nobody can innovate by himself without interaction from others. Individuals should work together towards a common goal. Within a company, people need to work together and this should also be the case within a university, research labs and public institutions. A regional innovation system is the interplay whose objective is fostering innovation at regional level (P. U. Cooke, M. G.; Etxebarria, G., 1998). Even at regional or national level, organisations cannot rely solely on their own knowledge. Effective global knowledge pipelines need to be established to exchange and develop knowledge with outside organisations (Bathelt, 2004). Therefore, a constant exchange and flow of information should exist between individuals and organisations at local, regional, national and world level.

A fundamental requirement for effective knowledge networking between two individuals is that some overlap in knowledge bases is needed in order to be able to interact, share, transfer, and create knowledge (Balland, Boschma, & Frenken, 2015). In other words, a minimum level of cognitive proximity is required (Nooteboom, 2000). Effective absorptive capacity relates to the collaboration aspect and is critical to the innovation capabilities of firms. Absorptive capacity is the ability of a firm to recognise the value of new, external information, assimilate it and apply it to commercial ends (Cohen & Levinthal, 1990). Absorptive capacity improves with a certain mutual understanding for collaboration and trust (Gulati, 1995), which relates to the overlap of knowledge bases or the cognitive proximity. Cognitive proximity between individuals refers to the degree of overlap of knowledge bases, or mutual understanding and trust: the higher the cognitive proximity, the greater the overlap of knowledge bases and understanding between individuals and organisations.

Knowledge stock is available at individual, firm or regional level. And the way to increase the degree of overlap with other knowledge bases, is by increasing our own knowledge stock, or said differently, by increasing cognitive proximity between individuals, firms, and regions that have a higher level or a different knowledge stock. Since regions are being assessed as a whole, the idea is to compare the sum of private knowledge stocks available in the region and then approximate the investment in R&D or spending in tertiary education among other indicators.

If the codified knowledge stock of Region A is similar to that of Region B, then the degree of knowledge overlap is said to be high and respectively the cognitive proximity between Region A and Region B is said to be close, which suggests high absorptive capacity across the two regions. Cognitive proximity is defined as the degree of overlap of all knowledge bases. Therefore, two regions of similar size and of similar economic structure, for instance the region of London and the region of Paris should have high overlap of knowledge stocks than for instance the region of London and the Land Saarland, since their role as an administrative and financial capital are simply incomparable. Therefore, the cognitive proximity of the region of London and the region of Paris can be said to be close.

These objectives and our own argument are based upon the distinction between codified and tacit knowledge stocks (Michael Polanyi, 1966). Codified knowledge refers to knowledge that can be and is readily articulated, codified, accessed and verbalised

(Cowan et al, 2000). This knowledge can be accessed in books, manuals, documents, videos or drawings and can, therefore, be easily transferred from one place to another. Knowledge such as discoveries in natural science is articulated and is universal in nature. It fosters the capacity to act across contexts and can therefore be readily transmitted through large distances (Nonaka & Krogh, 2009).

Tacit knowledge is knowledge that cannot or has not been written down (Michael Polanyi, 1966). In addition, it can be knowledge that people are not aware of but access it while performing a task (Nelson, 1982), and depend upon a temporal, spatial, cultural and social context (Cowan et al, 2000). Sometimes tacit knowledge is difficult or impossible to codify or just simply remains tacit in order to make it less accessible and transferable. At times knowledge remains tacit because access/transference costs are simply too high (Nelson, 1982). Tacit knowledge is tied to senses, tactile experiences, movement, skills, intuition, unarticulated mental models or rules of thumb (Nonaka & Krogh, 2009). Therefore, it can neither be readily accessed nor transferred over a distance. It is abilities such as riding a bicycle, or wine tasting, or recognising one face out of millions, which are acquired through practice and transferred by working together in groups from masters to apprentices.

The distinction between knowledge in its codified and tacit counterparts gained in importance with the rise of the regional innovation systems literature, since this type of knowledge is relatively sticky and the marginal costs of transmission rise steeply with distance (Cowan et al, 2000). Tacit knowledge is unique to an individual, an organisation or a region, and unlike codified knowledge cannot be copied (John Kay, 1999). Tacit knowledge can be shared and developed by working together but always takes a new form. The same codified knowledge has a different meaning in one region vis-a-vis another. For instance, despite all codified knowledge to develop business models such as Facebook and other social networks being available in Europe and Russia, these business models never took off in these places. They were only developed in Silicon Valley. Therefore there seems to be a tacit knowledge that is unavailable elsewhere.

This tacit knowledge can include attitudes towards entrepreneurship, conversations in society or groups that are crucial in achieving innovation. There are groups that maintain close conversations on new ventures, food, gastronomy, football, or events, cars, finance and economy. Anyone who has lived in different countries can tell the difference from one place to another, something similar to what Stiglitz (1999) experienced when he arrived to teach at Stanford: “One really felt the entrepreneurial spirit at Stanford. In the corridors and restaurants, there was constant talk of new enterprises, translating the advances in ideas into new products and new businesses”((Stiglitz, 1999): 39). Discussions, reflections and debates form, develop, and increase the tacit knowledge stock in a region. People can access these conversations by actually being there since it is sticky knowledge that can only be accessed through physical interaction with each other on a regular basis.

The complementary condition of tacit and codified knowledge gives rise to new knowledge. Both knowledge types dynamically interact with each other in the creative activities of individuals and groups (Nonaka & Krogh, 2009). Knowledge conversion is the process of interaction between tacit and codified knowledge, where subjective personal knowledge can be socially justified (Massey & Montoya-Weiss, 2006). Hence, the combination of codified and tacit knowledge makes knowledge unique (John Kay, 1999), and needs to be developed in combination, in order to avoid imbalances that might lead to myopia, excessive path dependence in the industry (Nonaka & Krogh, 2009), or inefficiencies in the innovation value chain. This is the main argument of this thesis.

An example of a manager in the technical clothing industry will further illustrate the point. She/he goes to trade fairs and interacts with trend setters at adventure sport contests, seeking ideas for new trends, interacts with the fashion trend setters, observing rituals, colours, attitudes that can provide hints on future trends. Then, she/he reflects on her/his own tacit knowledge in fashion design and marketing, on past successful projects and failures, and with codified knowledge such as technical capabilities of the industry to implement new types of products, variations of zippers, pockets, capabilities of membranes, thermal capabilities, logistics and production cycles.

Then she/he reflects again on her/his tacit knowledge to interpret this information and estimate the real capabilities needed to implement an effective innovation. Every industrial sector has developed its own specific tacit knowledge for delivery terms or tolerances, and therefore information given and tolerance provided by suppliers with respect to non-conformities differ substantially. What is a good in the textile industry might be unacceptable in the automobile industry, and vice-versa. Knowledge or practices developed in one industry may not be applicable in others. Nevertheless, leakage of information and knowledge are necessary from time to time since industrial sectors learn from each other sectors and apply this knowledge to successfully innovate.

Inditex has become the largest fashion retailer in the world by challenging industry conventions and by turning entrenched practices upside down (Buck, 2014). By applying the latest technology and logistics, Inditex avoids stock piles and builds fashion-to-demand just as the automobile industry produces cars that are already bought. This complementary continuous interplay of codified and tacit knowledge is needed in the correct proportions to successfully introduce innovations in any industry.

The suitable proportions of codified and tacit knowledge may however differ. Early in the life of a technology or a discipline, models and vocabulary need to be developed through existing and new tacit knowledge bases. This means that new technologies rely heavily on tacit knowledge and become more and more codified with maturity (Cowan et al, 2000). Moreover, the proportions of codified to tacit knowledge vary according to economic activities. Design activities tend to rely heavily on tacit knowledge, whereas natural sciences depend more on codified knowledge.

Our model is built upon the complementary model of codified and tacit knowledge of Nonaka and Takeuchi (1994) and applies it on Nooteboom's (2007) and Boschma's (2012) optimal proximity model. In an attempt to analyse the optimal cognitive proximity for innovation collaboration activities in the aviation industry, Boschma observed that while cognitive proximity is essential to increase absorptive capacity, too much proximity might be detrimental with regard to the novelty of the innovation that results from this collaboration, since high absorptive capacity alone does not say anything about the impact of innovation in the market.

Many authors elaborated on Nooteboom's findings, differentiating cognitive proximity from organisational, social, institutional and geographic proximity. They based their arguments on earlier literature findings and observed that when firms co-locate, there are positive influences on innovation activities, and that geographic proximity could balance out cognitive distance (Audretsch & Feldman, 1996). Others noted that geographic proximity loses its importance in the presence of social or institutional proximity (Breschi, Lissoni, & Malerba, 2003).

These findings confirm our hypothesis that the cognitive proximity paradox should take into account the complementarily of codified and tacit knowledge. It is precisely in the geographical, social, institutional or organisational dimension where we suspect that tacit knowledge is shared, exchanged, and developed (John Kay, 1999). Therefore, the proximity paradox can be optimised by emphasising cognitive proximity in the case of codified knowledge stocks and cognitive distance in the case of tacit knowledge stocks.

Cognitive proximity is usually applied to collaborations between firms (Broekel & Boschma, 2012). When applying these ideas to regions or clusters, we need to take into account the different development strategy of a region vs. a firm, and that regional diversity within a region will not per se stimulate regional development, since it might involve a too large cognitive distance between local firms (Asheim, Boschma, & Cooke, 2011). When constructing a regional competitive advantage, related variety is a key concept. It specifies that economic development is explained in terms of variety of sectors or the variety of technologies (Frenken, Van Oort, & Verburg, 2007). We could also take it to the individual level, where migrants bring different skills to the same tasks (Ottaviano & Peri, 2005).

In an exercise of translating concepts originating from the business world to regional economic studies, Navarro et al. (2011) observed differences between business and territorial strategies at three levels. First, territories have different strategies than businesses, since the aim of territories is to increase welfare rather than maximize profitability. Secondly, territories are different according to their clusters' and sectors' specialization, whereas the companies are different due to their market focus. Third, territories have participatory processes in the development of their strategy, whereas company's strategy development is usually developed by managers.

With regards to cognitive proximity applied to territories, we might think of industry sectors' that are technology-related. While companies need a certain cognitive proximity in terms of technology they use, a region should have sectors' that complement each other (Frenken, et al., 2007). Translating cognitive proximity at the individual level, people complement each other with different skills to the same task (Ottaviano & Peri, 2005), which should increase creativity and lead to innovation activity in the region.

Geographic proximity might balance out cognitive distance of tacit knowledge stocks because coordination costs are lower. These objectives and sub-objectives of the thesis lead us to the following hypothesis:

1.3. Hypothesis

In order to achieve our objectives, a set of hypotheses are laid out to ascertain whether or not greater openness in the regions leads to an improvement of innovation efficiency:

H1: Greater openness in terms of human capital leads to innovativeness

H2: A more heterogeneous tacit knowledge base resulting from inward migrations increases the innovation outcome of regional innovation systems.

H3: Even though the exchange of external codified knowledge stock needs a good absorptive capacity, openness is also beneficial in terms of innovations for countries and regions with low stocks of codified knowledge.

H4: Greater openness to global sources of human and social capital leads to wider development of creative industries.

H5: Openness as a tool to increase heterogeneity of the regional tacit knowledge base is more significant as a predictor of creative workforce than to predict innovations.

H6: The larger the geographic mobility of the migrants in the region, the more the migrants contribute important tacit knowledge.

The effect of codified knowledge stock in form of R&D investment is widely acknowledged in the literature. Romer (Romer, 1990) has shown the effect of investment in technology and R&D expenditure on economic growth, and challenged other research strands by arguing that there is a need to introduce technology as an endogenous factor for growth. R&D investment increases the standard in technology used in companies in the regions, which enable them to produce superior products and introduce new processes, which results in higher income and productivity growth.

The debate is focusing on the fact that R&D investment are costly and whether R&D requires achieving a critical level to be capable of generating technological progress (Bilbao-Osorio & Rodríguez-Pose, 2004). For instance, Foray and van Ark (2007) advocate for smart specialization strategies to be developed in Europe since not all R&D investment has the same effect in every region. This concept is a key element of the current EU 2020 plan, the European Commission strategy for innovation in the EU (Foray, 2009).

Bilbao-Osorio and Rodriguez-Pose (2004) found substantial differences in R&D investments and their effects in peripheral and non-peripheral regions. The latter are dominated by private firms, which ensure higher rates of return than R&D conducted by the public sector. In contrast, in peripheral regions R&D is dominated by universities, which often lack the know-how to transfer an innovation to a marketable product.

An important effect of R&D investment is the accumulation of codified knowledge stock that results in higher absorptive capacity. Authors have found that regional R&D investment reduces the distance from a region to the technology frontier (Griffith, Redding, & Van Reenen, 2003). It opens up the possibility to engage in distant collaborative activities.

Other authors stress the importance of R&D investment in ‘related varieties’ (Boschma & Iammarino, 2007; Frenken, et al., 2007). This stream of literature stresses the importance by bringing together different, but complementary pieces of knowledge as the basis for a regional competitive advantage.

Asheim and Gertler (2007) go even further with the concept of differentiated knowledge bases. They argue that the more diversified the business structure in the region, the more new ideas and knowledge spillovers occur that lead to relevant innovation outputs.

In fact, the economic success of cities were long attributed to its industrial diversification (Jacobs, 1969). The importance of global cities such as London, Paris, or New York to world economic growth and innovation have been widely recognized (Sassen, 2002). In addition, authors have focused on immigrants that contribute to linguistic and cultural diversity of a region, which leads to a more dynamic entrepreneurial spirit or regional innovation profile (Saxenian, 2002a).

Florida also stressed the importance of diverse and tolerant cities for innovation and their ability to attract high tech sectors (Florida, 2007). According to Florida, a diverse and tolerant society signals entrepreneurial and a spirit of endeavor that is important for the success of new or high-tech sectors. According to Florida, migrants in a region signals tolerance that attracts codified knowledge. Therefore, Florida acknowledged that it is likely that human capital, amenities, and openness to diversity play complementary roles in regional development (Florida, Mellander, & Stolarick, 2008), although the literature do not provide a theoretical approach to answer why these complementary roles are so important and how these complementary roles work.

Williams (2007a) theoretical approach is different and analyzed migrants role in knowledge transactions. This stream of literature does not focus on high-skilled migrants but state that all employed migrants have potential for knowledge transactions. Tacit knowledge is transferred through enfolded mobility’s (Williams, 2007b), these are networks of migrants that transfers effectively valuable tacit knowledge into the region. Nevertheless, the ability of the migrants to bring in their tacit knowledge is also dependent on the regions openness to external cultures and external ideas, or their cosmopolitanism.

Under normal circumstances investment performed in the regions of codified knowledge in form of R&D investment is usually in areas where some effectiveness to the industry is expected. Here, investment in R&D should decrease the cognitive distance to other knowledge bases of the same or related fields lying outside the region. Similarly, immigrants and especially groups of immigrants increase the heterogeneity of the tacit knowledge bases available in the region. Not only high-skilled, but also low skilled migrants are beneficial since through their tacit knowledge bases they might provide new approaches, ideas, and links to markets.

1.4. Research method

The answer to these hypotheses is based on a set of empirical studies. The studies will be based on a sound theoretical analysis to understand direction of causality. According to Nooteboom (Nooteboom, 2007), cognitive proximity between two actors improves absorptive capacity[1], while cognitive distance increases the novelty effect value of a novelty. This leads to the formulation of Nooteboom's optimal cognitive distance and Boschma's and Broekels's proximity paradox (Broekel & Boschma, 2012; Nooteboom, 2007). This thesis is based on these two concepts but it distinguishes between knowledge in codified and tacit pools. With this distinction in mind, the best possible combination is sought, emphasising cognitive proximity in codified knowledge pools and cognitive distance in tacit knowledge pools.

While the importance to increase the stock of codified knowledge was long acknowledged in the economic development literature (Romer, 1990), the concept of tacit knowledge and its importance has been recognized rather recently with the development of the regional innovation literature (Lundvall, et al., 2002). Our model builds on the importance of complementarities of both knowledge types (Nonaka &

[1] Absorptive capacity is defined as the ability of a firm to recognise the value of new, external information, assimilate it, and apply it to commercial ends (Cohen & Levinthal, 1990).

Takeuchi, 1994). According to Florida (2008), what shapes the distribution of human capital in the first place is the mix of establishing Universities, amenities, and openness to diversity in the region. While universities increase the codified knowledge stock, social and cultural diversity increases the tacit knowledge stock (Williams, 2007b). Both knowledge types need to evolve together (Nonaka & Takeuchi, 1994), since it avoids imbalances of having too much or too few of codified knowledge in relation to tacit knowledge (Cowan et al, 2000). Migrants are attracted by an open environment that let them contribute with their tacit knowledge (Williams, 2007a). this leads to, according to Florida, high skilled individuals being attracted automatically by a high and balanced stock of codified and tacit knowledge.

Given that tacit knowledge can only be shared by physically working together, e.g. from master to apprentice, the cognitive distance of tacit knowledge pools is considered only in a specific regional context. That is, immigration into a region is a sign that people from a different background enter a region, suggesting that the total cognitive distances across individuals and communities in a region increase. Moreover, inclusiveness indicators such as young people working in the labour market or female workers are analysed because an inclusive labour market signals higher total cognitive distances across individuals. For instance, Hunt (2008) and Niebuhr (2010) observed that more diverse regions are more innovative. In the case of the US, their data indicated that a one percentage point rise in the share of immigrant college graduates in the population increases patents per capita by 6%, with further positive spillovers in inventors resulting in an increase in patents per capita of 9-18% (Hunt & Gauthier-Loiselle, 2008). Many authors found a positive impact of immigrants to increased entrepreneurship in the region (Florida, 2007).

The first chapter of this work is an empirical analysis of codified and tacit knowledge indicators to get an idea of their influence on innovation indicators. The main task is to analyse as many indicators as possible and learn as much as possible about innovation input and output indicators. The chapter firstly analyses internationalisation indicators, i.e. indicators that enable the exchange of codified knowledge across borders (Bathelt, et al., 2004). These indicators are then compared with openness indicators, i.e. indicators that enable new tacit knowledge pools to enter the territory, in relation to the innovation output indicators. Special emphasis is laid on correlations between innovation input and innovation output indicators and their significance. This first analysis provides a first answer on the importance of diversity of tacit knowledge pools vis-a-vis international codified knowledge inflows. The analysis is based on a basic quantitative exploration to see which innovation input indicators show significant correlations with which innovation output indicators and whether openness indicators are important.

The second part of the research is based on earlier findings and complements the empirical analysis through a principal components regression analysis. The research first selects a number of openness indicators at regional level. Thereafter, the indicators that provide information on the stock of codified knowledge available in the region are selected. In this manner, we have information not only on the tacit knowledge stock, i.e. openness, but also on the codified knowledge stock, e.g. R&D or investment in tertiary education. The second chapter selects creative workforce as the output variable.

Creativity and innovation are two closely related concepts. Creativity is the production of new ideas, whereas innovation is the introduction and application of new ideas, processes or procedures (Rank, Pace, & Frese, 2004). Creativity is more linked to the generation of the idea while innovation is more linked to its implementation. Moreover, creativity differs from innovation in that it is truly novel. Innovations on the other hand can be new to the group but can be based on ideas that are transferred from a different organisation.

Romer (1990) view creativity as an important element to produce new technologies and products, which lead to economic growth. The production of new technologies and products that lead to economic growth are innovations (Archibugi & Iammarino, 2002). Creativity is closely related to knowledge, and quests society's norms and values. Many businesses today, especially those that are exposed to global competition, demand employees that have the ability to "think outside the box", i.e. people who have the ability to quest procedures and products that have become the norm in companies (Adair, 1990). The idea is that creative employees may develop business innovations that lead to a competitive advantage. At the regional level, a competitive advantage of several companies results in economic growth.

In sum, the concept of creativity is more related to the characteristics of a person or a small group of employees working together to produce novel and useful ideas, whereas innovation is based on creative ideas as their basic elements (Bassett-Jones, 2005). Innovation in an organisation is the successful implementation of creative ideas within the organisation (Amabile, 1988).

Creativity is measured by the actual workforce in creative industries, since creativity is to some extent an individual cognitive process (Anderson & King, 1993). Nonetheless, it nurtures itself in the environment in which the creative persons live. Therefore, it is of vital interest to test both creativity and innovation, since both seem to complement each other and we can test for the different optimal proportions of tacit and codified knowledge.

In line with the model applied in this thesis, we would expect that creativity is based more on tacit knowledge while innovation more on codified knowledge. This is because tacit knowledge is based more on knowledge that is soaked up in the regional context from an infinite number of impossible to codify sources. Innovation on the other hand is based on a stock of codified knowledge that is built up through investment in R&D and tertiary education, among others.

A principal component analysis is first used to see whether the two principal components, i.e. tacit and codified knowledge stock, are identifiable as the two principal components. Whenever both happen to be the principal components, these are used to calculate the regression function. The analysis includes data from the NUTS 2 and NUTS 1 regions of the European Union[2]. A second paper then analyses innovations as output. In this case, five different innovation indicators representing different types of innovations are tested. Patents for instance are one form of registering innovations but are not the only one. Not all patents make it to the market and not all industries patent in the same way. Therefore, the principal component regression analysis is performed on five different output indicators that take into account the variety of forms that an

[2] The NUTS classification is an EU classification for regions. Most regions are NUTS 2 but in some cases NUTS 1 (e.g. Region of Brussels) have been selected as they seem to be more appropriate for consideration as a Regional Innovation System.

innovation can take. Here, the principal component regression analysis is performed on a panel that contains data from 2010 to 2012 on the autonomous communities in Spain.

1.5. Thesis structure

The structure of this thesis consists of an introduction, three main chapters and general conclusions. After the introduction, the first chapter lays the theoretical foundation of this work but also includes a preliminary quantitative analysis to understand the relationship between the innovation input indicators and the innovation output indicators. Given that more data are available at national level, data were analysed at that level in order to include the highest possible number of indicators. The research was mainly focussed on better understanding the innovation value chain, which is defined as the process from idea generation, idea development and the diffusion of developed concepts (Hansen & Birkinshaw, 2007). More specifically, this chapter intends to throw light on the influence of global knowledge pipelines in transporting codified knowledge and the relevance of openness in bringing tacit knowledge into the territory. The quantitative analysis includes significant correlations using the Pearson technique performed between the innovation input and the innovation output variables.

The following two chapters develop the interpretative model with an advanced quantitative analysis based on a principal component regression analysis. The openness variable and its effect on the creative workforce at European level is analysed in the first of these two chapters. This research is performed using 2000-2008 Eurostat data. The other chapter analyses openness variables and their effect on innovation output using the Spanish Statistical Office's (INE) 2010-2012 data for Spain. The three chapters together help us to test the hypotheses mentioned above. Results from all chapters have been presented at international conferences.

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CHAPTER 2

OPENNESS, INTERNATIONALIZATION, AND INNOVATION EFFECTIVENESS IN NATIONAL INNOVATION SYSTEMS

2. Openness, Internationalization, and Innovation Effectiveness in National Innovation Systems

2.1. Introduction

According to Acemoglu & Robinson, authors of "Why Nations Fail" (ACEMOGLU & ROBINSON, 2012), pluralism, in which inclusive political institutions allow broad participation, is key to achieving higher economic growth. An explanation to this relationship could be based on the role of tacit knowledge that might be activated through pluralism (Michael Polanyi, 1966). Williams (2007b) exposed the ways tacit knowledge is transferred taking international migration as example and how it benefits the region not only by means of transfer of skills, but also through capital and knowledge transfer.

The variety of tacit knowledge brought in by international migration benefits the economy by means of innovations and creativity. Empirical studies determined that economic growth concentrates geographically and is fuelled by the ability to foster an open, dynamic, personal and professional urban environment that attracts people, business and capital (Florida, 2002b). Our paper offers a theoretical explanation of this relationship, based on the knowledge flows that influence innovation performance in a National Innovation System (NIS). We analyze the role of external codified knowledge flows in 'internationalization', as well as the role of tacit knowledge flows within NISs, which we refer to as 'openness'.

There is no clear definition in the literature of the concepts of 'internationalization' and 'openness' related to the field of economics. Internationalization is often referred to the involvement of enterprises in international markets. For instance, the OECD refer in its internationalization studies to access of companies to foreign markets and the barriers they encounter (OECD, 2009). Business that are active internationally need the ability to think globally and act strategically different in each market on the basis of their own beliefs, values, behaviors (Root, 1998).

Other internationalization studies deal with R&D, which often refer to collaboration of entities through distance, analyzed through patent citations or patent cross-border ownership (Criscuolo, Narula, & Verspagen, 2005). Through this means, internationalized regions receive codified knowledge from outside by means of the exchange between entrepreneurs, researchers and managers, among others. Nevertheless, internationalized regions are not necessarily open regions, and vice versa. For instance, Japan has very internationalized businesses sector, but this does not mean that the country can be considered 'open' in our terms (Lawrence & Krugman, 1987).

The concept of openness in economics is mostly applied to trade policy measured in imports and exports as percentage of the country's GDP (WorldBank, 2015). Proxies for openness include trade dependency ratios and the rate of growth exports (Edwards, 1998). In latest years, however, openness has increasingly been mentioned in relation to innovations. The concept of open innovation (Chesbrough, 2003), which refers to the firms strategy to use external and internal ideas and paths to market, has generated a fruitful debate in the literature dealing with sourcing, acquiring, revealing and selling of innovations (Dahlander & Gann, 2010).

The openness concept applied here is more related to socioeconomic phenomena. The importance of openness for a diversified economy was already observed by Jacobs (1969), which led to the term Jacobs' externalities. It refers to the observation that cities with diversified set of industries are characterized by high economic growth as a result of the creativity that a diversified industrial structure generates. Nevertheless, it is only in the last decade growing in importance in economic development, more concretely with Florida's (2002a) publications on regional development and the literature on related variety (Frenken, et al., 2007).

Openness to experience is one of the domains to describe human personality (McCrae & John, 1998). Individuals who are open are open to new experiences, tend to have more liberal views and have positive relationships with creativity, intelligence and knowledge. For instance, people who score low on openness tend to be more conservative, authoritarian, ethnocentric and have prejudiced views (Laythe, Finkel, &

Kirkpatrick, 2001). At an aggregate level, individuals form the personality of a country and its preference for its degree of openness.

According to Florida (2008), the openness of individuals to diversity plays a key role also in territories as it shapes the distribution of human capital. Increased diversity among individuals by means of enlarged immigration increases productivity through their potential complementary skills (Ottaviano & Peri, 2005).

Since our hypothesis is based on the distinction of codified and tacit knowledge, juxtaposing internationalization and openness allows us to differentiate clearly these two concepts in relation to the knowledge that is conveyed in the region.

The theoretical concepts presented here are corroborated by preliminary statistical observations. Correlations of the two knowledge types are compared to determine if codified and tacit knowledge complement each other. Both knowledge types are analyzed by relating codified knowledge to internationalization and tacit knowledge to openness in the NIS.

Our investigations provide theoretical concepts that enable us to determine both the importance of internationalization and openness in the innovation process through empirical analysis, and the direction of causality. Internationalization is an ambiguously used term in the literature. In the economic field it mostly refers to sales generated outside the home country or the value of exports in percentage of the GDP. We define ‘internationalization’ in terms of the degree of knowledge exchanges that are predominantly codified, such as outward FDI, collaborations with companies and institutions across national borders, temporary exchanges of qualified workers to exchanges skills among others. Simultaneously, we define ‘openness’ as the degree of knowledge exchanges that are predominantly tacit, such as inward FDI, immigration or inclusiveness of the labor market.

1) Our first hypothesis is that greater openness improves innovation performance.

2) Our second hypothesis is that innovation performance depends on the complementary roles of tacit and codified knowledge.

Our hypotheses are based on the innovation paradox of Broekel and Boschma and Nooteboom (Broekel & Boschma, 2012; Nooteboom, 2007), who observed that cognitive distance between knowledge bases needs to be close enough to favor collaboration and exchange, but not so close that it leads to lock-in. In other words, cognitive distance should be reduced to increase absorptive capacity - the 'ability to recognize the value of new information, to assimilate it, and apply it to commercial ends' [(Cohen & Levinthal, 1990): 128] -, and enable the flow of distant, codified knowledge, while cognitive distance of geographically close, tacit knowledge should be increased to improve innovation performance.

In relation to collaboration in innovation across national borders, the European Innovation Scoreboard commissioned a research study on the relationship between innovation and internationalization. The study shows a clear association at all levels of analysis, and in particular between innovation and outward Foreign Direct Investment (FDI), and innovation and foreign human resources (Filippetti, 2009). However, the study did not provide a theory or proof of the direction of causality. As a consequence, policies in this field cannot be clearly formulated. Our detailed analysis of the knowledge types involved and their interactions provides more information and enables a clearer understanding of the interactions.

The role of the knowledge transactions across borders in innovation systems has not received the attention one would expect in literature, given the role of globalization in the economy and the recognition it has received in European Commission (EC) policy documents. The Lisbon Agenda referred to globalization as one of the four most important challenges for the European Union (EU). Globalization, defined as the increasing economic interdependence of national economies across the world, is regarded as key to the process of transformation to a knowledge and service economy; it is as profound as the earlier shift from agriculture to industry (Communities, 2008).

Bathelt et al.'s (2004) concept of knowledge creation in clusters and its relation to spatiality are most prominent in literature on external linkages. Knowledge creation in a successful cluster is based on the local 'buzz,' which represents the informal information exchange within a cluster which is fueled by global knowledge pipelines. Local buzz and knowledge arriving through these global pipelines are complementary and lay the foundation for a competitive cluster. Furthermore, along with the phenomenon of globalization, researchers have observed that the more knowledge-intensive an economic activity, the more the activity concentrates in a few locations around the world (Maskell & Malmberg, 1999).

A logical explanation of this phenomenon may be built on Polanyi's (1966) essay, "The Logic of Tacit Inference." He describes the characteristics of knowledge, referring to tacit knowledge as knowledge that cannot be written down, whereas codified knowledge is written down in a codebook [(Cohen & Steinmueller, 2000) see also (Malerba & Orsenigo, 2000b)]. Both knowledge types are necessary because knowledge is the result of a continuous dialogue between tacit and codified knowledge (Nonaka & Takeuchi, 1994); they are complementary during the process of their creation (Nelson, 1982). An idea develops through the interaction between individuals and the exchange of knowledge in communities. The more economic activities are based on knowledge and the easier it is for economic agents to access codified knowledge from anywhere in the world, the more important tacit knowledge becomes because it cannot be accessed remotely.

Tacit knowledge leads to geographical concentration because its exchange requires frequent face-to-face meetings (D. Parrilli, 2011). Hence, globalization, knowledge intensity of products and services, and regionalization of the innovation process are related forces.

However, the flow of knowledge may be conditioned by the absorptive capacity - the ability to identify, assimilate and exploit knowledge from the environment (Cohen & Levinthal, 1990) - of the Regional Innovation System (RIS). Nooteboom (2000) claimed that an 'optimal cognitive distance' is needed to favor innovation. According to Boschma and Frenken (R. F. Boschma, K., 2010), cognitive distance refers to the degree of overlap of the knowledge bases of two actors. Nooteboom acknowledged that cognitive proximity between collaborative agents ensures high absorption capacity, but observed that if knowledge bases are too similar, the likelihood of a more innovative recombination is lower than when two divergent knowledge bases measured in the degree of overlapping between both knowledge bases are merged. There is an apparent trade-off between increasing absorptive capacity by reducing cognitive distance to external knowledge bases, and the need for a certain cognitive distance to enable an innovative recombination of that knowledge. This finding led to the formulation of the proximity paradox [(Broekel & Boschma, 2012): 7].

> "While proximity may be a crucial driver for agents to connect and exchange knowledge, too much proximity between these agents on any of the dimensions might harm their innovative performance."

Our hypotheses are based on the assumption that this paradox can be explained by differentiating the codified part of knowledge from the tacit part of knowledge. Depending on the knowledge type involved (codified or tacit), cognitive distance between knowledge bases must be reduced (through codified knowledge investment) or increased (through openness) to reach the optimal proportions of each knowledge type and improve innovation performance.

When applying the cognitive proximity paradox, i.e. proximity may be a crucial driver for agents to connect and exchange knowledge, but too much cognitive proximity between agents might harm their innovative performance at the same time, to the territory, we need to take into account that the concept of Nootebooms (2000) cognitive proximity has been applied to collaborations between two companies, which in this case need to be adapted to regional territories. We may differentiate three groups of aggregations where the concept of cognitive proximity can be applied and studied: a) individuals at the company level, i.e. workers; b) individuals at the regional level, i.e. inhabitants, and c) companies in the region. Our thesis is focusing on cognitive proximity at the individual level (c), i.e. workers and inhabitants in regions.

With respect to companies in the region, Asheim et al. (2011) adapted the idea of the cognitive proximity paradox to territories. The idea of the cognitive proximity paradox is a concept deriving from the analysis of collaborations between firms (Nooteboom, 2007), where a balance of cognitive proximity is needed to increase absorptive capacity and cognitive distance to increase the novelty of the interaction is needed.

Neither regional firm diversity stimulates regional development nor regional specialization per se does, i.e. high cognitive proximity between firms at the regional level might lead to industry myopia (Asheim, et al., 2011). According to Asheim et al. (2011), the cognitive proximity paradox should be interpreted in a way that companies -

at regional level - should specialize in technology-related sectors to benefit from different but complementary intended or unintended knowledge spillovers.

Similarly, when translating the cognitive proximity concept to the firm level, a diverse cultural background represents a diverse tacit knowledge base that needs to find a common codified knowledge stock. Ottaviano and Peri (2005) observed how immigrants increase regional productivity since immigrants have complementary skills to native born because they bring different skills to the same task. For instance, employees may perform the same research but with different approaches. In addition, a common corporate culture and vision may be shared among a diverse employee structure to increase innovativeness.

Translating it to individuals at regional level, citizens need to share a common rule book and values that enable tacit and codified knowledge exchanges among them. Diversity in terms of age, gender, race, religion, professional trajectories, life experiences and nationalities, need to be complemented by shared communication and basic rules (Niebuhr, 2010). There could be costs of diversity that results from the inability to agree on common public goods and public policies in the region (Alesina & La Ferrara, 2005). Therefore, democratic and participatory processes in diverse populations might be extremely important to find a common ground accepted by all the groups and individuals with little conflict. Cognitive distance should be interpreted in this way, once values, basic norms, and theoretical frames are understood and shared, diverse cultures are in condition to lead to higher innovation and creativity levels (Alesina & La Ferrara, 2005).

Investment in codified knowledge decreases the cognitive distance to other codified knowledge bases, such as between NISs and outside NISs; this leads to higher absorptive capacity. Knowledge travels large distances at low transaction cost. Tacit knowledge bases, however, can only be exchanged locally, through face-to face contacts (Hildrum, 2009; D. Parrilli, 2011). The larger the geographic distance, the less tacit knowledge can be shared. Tacit knowledge cannot travel easily through space; it is associated with very high coordination costs such as misunderstandings that require frequent meetings. At the local level, however, coordination costs are less important; they are counterbalanced by the benefit of achieving a more innovative recombination of divergent knowledge bases.

Tacit knowledge, which plays a key role in a competitive innovation system, is characterized by its limited geographic mobility. Therefore, the National and the Regional Innovation System is a key concept that is reinforced by the increased knowledge intensity of products and services on one hand, and the globalization process on the other.

In the next chapter, we review the NIS and RIS literature to understand the reasons that have led to the rich production of literature in this field. In Chapter 3, we review the literature on knowledge creation that leads to innovation in firms and organizations to understand the creation and development of knowledge that leads to innovations; in Chapter 4, we review literature on the role of internationalization and openness in the innovation process to connect it to the former two chapters and that will lead us to build our model. In Chapter 5, we describe our model and present our first findings based on 2008 national data from the European Union. We determine the drivers of innovation by relating them to innovation outputs. Chapter 6 presents our conclusions and identifies future lines of research.

2.2. Systems of Innovation

Systems of Innovation can be related to the region or the nation. The concept of the National Innovation System (NIS) is the idea that government policy at the national level should play an active role in knowledge management and learning in catching-up economies. It is defined as the interaction of firms and the knowledge infrastructure taking into account the wider setting at the national level (B.-A. Lundvall, 2007). A Regional System of Innovation (RIS) is based on the idea that a relationship can be established between knowledge actors and places (Lorentzen, 2009). Cooke (1992) introduced the idea that within a state, a great diversity may exist that supports the need for a more differentiated analysis at a sub-national level. Prior to this proposition, innovation systems were mentioned in relation to the nation state.

Freeman noted that the NIS concept developed with increasing empirical evidence about the relationship in accumulation of industrial R&D and innovation in the US, Japan and Europe (Freeman, 1995). The concept of a NIS is "a system of innovation is constituted by elements and relationships which interact in the production, diffusion and use of new, and economically useful, knowledge and that a national system encompasses elements and relationships, either located within or rooted inside the borders of a nation state" [(Lundvall, 1992): 2].

Apart from formal R&D, it became evident that the success of innovations depended on a wide variety of other influences (Freeman, 1995), such as the education systems, the labour markets, the financial markets, the intellectual property rights, competition and welfare regimes many of them set up and ruled at national level (B.-A. Lundvall, 2007). The interaction of firms and the knowledge infrastructure with the objective to innovate is largely influenced by this setting. Depending on the national strategies, countries may specialize on the STI mode of innovation based on using and creating codified knowledge or on the DUI mode of innovation based on tacit knowledge circulation (Jensen et al, 2007).

In addition, the national setting has an influence on the type of innovations with regards to incremental innovations and radical innovations. In the case of incremental innovations, such as cost cutting or feature improvements in existing products or services (Leifer, 2000), the importance of institutional variety and localized learning is not that great than for radical innovations. Radical innovations are completely new products that may substitute existing ones, such as the electric bulb substituted the candle. Incremental innovations would be improvements of the candle such as improvements in light yield, less wax consumption, better smell or cost reductions in production, but radical innovations introduces a totally new product line that can make existing ones obsolete. Radical innovations contain an element of creative destruction, problems of structural and social adjustment can be great and national governments might influence with standards and regulations the degree of radical innovations taking place in the country.

On the other hand, one of the important aspects of the regionalization of innovation concept is that economic specialization, by means of worldwide production systems, and economic activity that is increasingly based on knowledge (increasing the importance of geographically bounded tacit knowledge) are the main reasons that globalization and regionalization reinforce one other.

According to Cooke (2001), a Regional Innovation System (RIS) occurs if and when the regional production structure (the 'knowledge exploitation subsystem') and the regional support infrastructure (the 'knowledge generation subsystem') are systematically engaged in interactive learning. Under this rather strict definition, only four of 11 European regions analyzed in the EC-funded 'Regional Innovation Systems: Designing for the Future' (REGIS) project could claim to be a RIS. While Cooke claims that the existence of a RIS is the exception rather than the rule, others state that all regions have some kind of a RIS in place (Bunnell & Coe, 2001), referring to the RIS as part of a global production network (GPN).

Advocates of GPNs claim that less consideration has been given to the potential of information, telecommunication and transportation technologies to link people and places across the globe and increase geographical, societal (various societal mechanisms and structures that motivate actors to share goals) and cognitive (cultural and technological mindsets that enable common understanding) proximity.

Regional development rather depending solely on endogenous growth is the *dynamic outcome of the complex interaction between territorialized relational networks and global production networks within the context of changing regional governance structures* ((COE, HESS, YEUNG, DICKEN, & HENDERSON, 2004): 469). Local and regional policies should enable access to global knowledge, by focusing on societal mobility resources (infrastructure), or relational capabilities of local firms (language and technology skills).

Our chapter focuses on the role of internationalization vs openness in the NIS in the form of networks and relationships, building on the above-mentioned less developed case and taking into account the role of global networks in the form of physical presence at the national level—such as immigration or the establishment of foreign firms in an NIS. A first, exploratory, analysis will be made at the national level since more data is available at that level, that will be complemented in chapter 3 and 4 with analysis of Innovation Systems (IS) at the regional level. Internationalization can be the result of activities of innovation collaboration with companies located in foreign countries, outward Foreign Direct Investment (FDI), or participation in expert exchange programs. Openness interferes with the geographically bounded tacit knowledge base, as globalization brings different knowledge bases into the NIS through enfolded communities (Williams, 2009).

Because tacit knowledge is immobile by definition since it requires body-to-body contact (B.-A. Lundvall, 2007). openness refers to the idea that traditional non-native aspects that are available locally increase the cognitive distance of the tacit knowledge base. We interpret the increased cognitive distance as the presence of heterogeneous tacit knowledge bases. By merging divergent tacit knowledge bases (i.e., increasing the cognitive distance of tacit knowledge) (Nooteboom, 2007), ISs can increase innovative performance. Immigration, whether or not it is recent or highly qualified, is a typical example, as is inward FDI - bringing in new working methods into the country—or variables that provide us with hints on the acceptance levels of foreign-sourced ideas.

Moreover, an inclusive economy may indicate an open economy, because no groups of society are left out; inclusiveness can increase the distance of tacit knowledge by bringing new ways of thinking into the NIS. In many European countries young people, women, or minorities are being left out of the labor market; including them could increase the innovation capacity and creativity of the NIS.

Another valuable aspect of our analysis is that it offers a dynamic approach. The regional economist may take into account the economic development stage of a territory, prioritizing codified knowledge investment or tacit knowledge investment according to the characteristics of the RIS. For instance, regions that are catching up can be differentiated from highly innovative territories. Such an approach addresses criticisms that RIS theory is too static (Uyarra, 2010).

In the next section, we provide a detailed description of the knowledge bases involved in the innovation process.

2.3. Knowledge in the Innovation Process

Empirical results show innovation and economic growth figures are strongly correlated in EU regions. Input variables of innovation, including public and private investment in research, development, and innovation (R&D&I) with a value of 0.87, are strongly correlated to innovation output indicators including patents and publications (Navarro, 2011). Input variables refer to knowledge that precedes innovation (Parrilli, 2013); because innovation activity is strongly correlated to economic growth,[3] policy and investments in firms to increase productivity. Investment in education, research, and development is dedicated to the creation of knowledge to enable innovation to take place. To that end, it increases sales, profits, and economic growth at the RIS level.

Knowledge can be embedded in the region or reside externally. According to Polanyi (Michael Polanyi, 1966), it can be tacit or codified; the process of acquiring tacit

[3] Economic growth is one of many beneficial outcomes of innovation that can also help in reducing the resource intensity of the economy or be related to societal improvements. However, economic growth is probably the greatest incentive for actors to engage in innovation.

knowledge is equivalent to the process by which humans orient themselves in unknown territory and make sense of the world. Cultural misunderstandings are typical examples of the results of different tacit knowledge bases. People perceive particular aspects of new phenomena unconsciously. Polanyi argues that sharing of tacit knowledge is about people jointly creating a social environment. It is about people assisting one another in discovering new things and in solving new kinds of problems. Several forms of communication and interaction—such as the exchange of educational textbooks and manuals, skillful instruction, demonstration, imitation, and the accumulation of individual and shared practical experience — play important and complementary roles.

Codified knowledge is knowledge that has been written down; its principles reside in codes, rules, and procedures in textbooks. Everything that is articulable is codifiable, and everything articulated is codified. Lundvall et al. (2002) classify individual knowledge into 'know-what,' 'know-why,' 'know-who,' and 'know-how.' 'Know-what' are facts, 'know-why' are laws in motion in nature, 'know-who' is the social ability to communicate and co-operate with different kinds of people, and 'know-how' is the ability to do something. While 'know-what' and 'know-why' may be obtained through reading books, attending lectures, and accessing databases, the two other categories are rooted in practical experience. These types of knowledge are only partly codifiable; they are typically developed and kept within the borders of the individual firm.

Haruyama (2009) explains the knowledge relationship with an example from the biotechnology sector. He states that codified knowledge is the activity of publishing in journals; tacit knowledge is its implementation. For instance, the invention of hybrid corn, a superior variety, was not immediately adaptable to other locations. Creating adaptable hybrid corn required a superior knowledge of the technique and the location. The more experience was gained through adapting corn, the higher the tacit knowledge that was required to successfully adapt the corn to the location. Tacit technology is the ability to use and create new technologies.

Nonaka and Takeuchi (1994) suggests that knowledge is created and applied through a process of social interaction in which tacit knowledge is shared by socialization, translated into explicit knowledge, combined with other elements of explicit knowledge, and finally internalized into tacit knowledge.

But tacit knowledge is not only about skills and knowledge transfer from the highly skilled. Any person is knowledgeable and may have distinctive tacit knowledge that may be highly appreciated in the region. For example, it is the case of the investment banker in London with tacit knowledge about the Italian public sector, or the case of the agricultural products marketer in Spain with tacit knowledge on the agricultural industry in Algeria. Individuals not only transfer embrained and embodied knowledge, based on the individual skills and cognitive abilities and experiences derived from the physical presence, but also a truncated version of encultured and embedded tacit knowledge that are knowledge that derive from socialization and knowledge that is shared in specific language systems and culture (A. M. Williams, 2007b). Through enfolded mobilities (Williams, 2009), networks of minorities are able to offer versions of tacit knowledge from non-endogenous or non mainstream social capital.

Complementarities of tacit and codified elements of knowledge are often what matters most, a fact nearly all authors stress in their analysis (COE, et al., 2004; Cohendet et al, 2000; Nonaka & Takeuchi, 1994; Michael Polanyi, 1966). While some NISs or firms may rely on one type of knowledge more than another (depending on their economic specialization and development stage), they cannot rely on one knowledge type alone. In fact, many authors who have theorized on the optimum balance of tacit and codified knowledge (AMIN & COHENDET, 2004; Jensen, Johnson, Lorenz, & Lundvall, 2007) stress the impossibility of substitution.

Distinguishing between tacit and codified knowledge in relation to innovation systems is important with regard to geographic mobility. Globalization, encouraged by the intrusion of advanced technologies in economic activity—mainly information and communication technologies (ICT) and transport—together with the transition of the economy towards a learning economy (Lundvall, et al., 2002), has made mobile codified knowledge more accessible and caused knowledge creation to be increasingly dependent on immobile tacit knowledge. The more knowledge intensive economic activities are, the more they concentrate in a few locations around the world (Maskell & Malmberg, 1999).

Access to codified knowledge does not necessarily mean that a firm is able to make productive use of it. Cohen and Levinthal (1990) refer to 'absorptive capacity' as the capacity as a firm's ability to identify, assimilate, and exploit knowledge from the environment. By investing in R&D, a firm increases its knowledge base and reduces its cognitive distance from the knowledge bases of other firms and organizations as knowledge bases increasingly overlap. The presence of well-developed internal capabilities and resources in the form of infrastructure, education, universities, trained human resources, and other manufacturing sites gives the firm the tools to enhance their absorptive capacity and enable the exchange of distant codified knowledge, thereby further increasing the national knowledge base. However, the greater the cognitive distance, the higher the coordination costs and the need for local collaboration. Researchers have observed that a minimum cognitive distance is required to ensure a novel recombination of knowledge bases (Broekel & Boschma, 2012).

Nooteboom's (2007) research on strategic alliances of firms finds that the innovative performance increases when resource heterogeneity is combined. Nooteboom interprets resource heterogeneity in terms of the cognitive distance between the firms that hold these various resources. However, large cognitive distance requires frequent meetings, resulting in reduced geographic scope of the knowledge exchange. Proximity of cognitive distance between actors increases absorptive capacity in firms or regions. At the same time, over-proximity can result in knowledge lock-in. In his empirical work, Nooteboom argues that in the case of exploration activities, the need for cognitive distance is more important than in exploitation activities. The more knowledge involved, the larger the cognitive distance needed to generate novelties.

Broekel and Boschma (2012) further elaborated on this idea, distinguishing four forms of proximity: cognitive, geographical, social, and organizational. They found interesting results from case studies in the Netherlands aircraft industry. Geographically close firms that have divergent knowledge bases are likely to increase firms' innovation performance. Therefore, the effect on innovation activity of reducing cognitive distance between actors is unclear. It reduces coordination costs, but the potential for novel innovative recombination is also reduced. From our review of the literature, we formulate the following theoretical application:

> Cognitive distance of codified knowledge bases should be reduced to increase absorptive capacity and enable the flow of distant, codified knowledge. At the same time, total cognitive distance of tacit knowledge bases should be increased to take advantage of geographically close, but heterogeneous tacit knowledge bases.

Internationalization and openness are relevant in both processes; their part in the innovation process will be explained in more detail in the next chapter.

2.4. Global Knowledge Sources in the Innovation Process

The European Innovation Scoreboard commissioned a study investigating the relationship between innovation and internationalization (Hollanders, Tarantola, & Loschky, 2009). All variables analyzed, particularly outward FDI and international human resources (HR) have shown strong correlation with innovation output variables. The reasons why firms invest in foreign countries are manifold and differ among industries, type of firms, countries and fluctuates over time (Lipsey, Ramstetter, & Blomström, 2000). It could be to exploit or transfer firms' resources to a country or to access resources in the foreign market such as market intelligence, technology know-how, management expertise, and notably various kinds of knowledge (Kolstad & Wiig, 2012).

Regarding international human resources there are few studies available mainly on high skilled migration. Saxenian (2002a) analyzed the effect of foreign-born engineers and scientist in the Silicon Valley and how they benefit with their skills, know-how and capital, but also how they create social and professional networks to start technology firms. Especially Willams (2007b) investigated these networks ('enfolded mobilities') by skilled but also non-skilled migrants and their knowledge transfers and contributions in social capital in the host country

The apparent relevance of global knowledge flows in the innovation process and the significant knowledge gaps that persist in this area are not reflected by research activity.

Only 0.1%–3% of all innovation papers is related to internationalization,[4] and even less are related to openness. Our work examines the external role in RISs by differentiating between internationalization and openness. The benefit of the global sources of knowledge in regionalized innovation systems in our model is twofold. On one hand, ISs establish networks to receive external knowledge in codified form, based on global knowledge pipelines (Bathelt, et al., 2004). On the other hand, ISs open up to improve the tacit knowledge base locally, increase the cognitive distance internally, and allow the merger of distant cognitive, but geographically close knowledge bases to create innovative reconfigurations [based on (Broekel & Boschma, 2012)].

Literature on innovation and global knowledge flows can be distinguished according to its study of the firm, the cluster, or the innovation system (national or regional) (Carlsson, 2006). Moreover, analyses have developed around certain concepts that can be described as the tools or the conditions through which knowledge is conveyed, including global commodity chains (GCCs), global value chains (GVCs), and global production networks (GPNs) (Yeung, 2011). Most research is based on Bathelt et al.'s (2004) exercise on clusters and global knowledge pipelines. Two information exchanges—local 'buzz' and global knowledge pipelines—form complementary sources of information that lay the foundations for a competitive cluster. More specifically, local 'buzz' is the continuous information and communication exchange due to accidental or organized meetings, face-to-face contacts, co-presence, co-location of people and firms, and even gossip and rumors. This leads to a similar interpretative scheme and mutual understanding of new knowledge and technologies. The main feature of local 'buzz' is that it is received almost automatically and spontaneously and leads to a fine-grained information transfer. Knowledge exchange through global knowledge pipelines occurs consciously and systematically; it needs trust and time and is therefore costly.

Moreover, communication through global knowledge pipelines is characterized by great uncertainty. Common institutions have to be built up and procedural rules defined with constant revision and refinement. Global knowledge pipelines are embedded in different cultural environments and socio-cultural settings. They may protect clusters from over-

[4] Around 0.1% of innovation titles in an EBSCO literature search are related to internationalization, and about 3% in Google Scholar text search. However, literature on innovation and internationalization is steadily increasing, with higher percentages for latest article searches.

embeddedness (too close a linkage between firms), which may result in knowledge lock-in. External linkages may serve as fuel, even in worldwide clusters of excellence, to develop new ideas and serve as a pool of external knowledge. The larger the number of firms in a location, the more vibrant and valuable the local 'buzz,' which increases the potential to establish a well-developed global knowledge pipeline and in turn makes the local 'buzz' more valuable and refined.

This dominant stream of literature focuses on the acquisition of external knowledge in codified form. ISs are by definition incomplete, since many, if not most, relevant networks, components, and functions for innovation in regional firms are extra-regional; correspondingly, the probability that local ties can offer all complementary resources is low. Hence, IS knowledge development must be complemented with external knowledge. The degree of knowledge that can be transported through the pipelines depends on the sophistication of the knowledge pipelines (as analyzed by the GCC, GVC and GPN concepts), and the absorptive capacity of the IS. The lower the cognitive distance of the IS to the outside world, the better the flow of codified knowledge through global knowledge pipelines (Nooteboom, 2007).

In our previous chapter, we discussed the complementary role of codified knowledge and its tacit counterpart. With increasing investment in codified knowledge, tacit knowledge can be activated within the IS, for instance through greater inclusiveness—integrating minorities, young people or women—or by means of an increasingly mobile labor market. Further development induces distant knowledge collaboration, which increases the knowledge base of the IS. With increasing development of codified knowledge fueled by distant collaborations, the proportion of codified knowledge may increase. Therefore, tacit knowledge also needs constant development and upgrading through external sources.

Given the importance of tacit knowledge to the competitive position of an IS (particularly the RIS), as discussed in this and the next chapter, it is particularly critical that all its available sources are exploited. Hunt and Gauthier-Loiselle (2008) and Niebuhr (2010) have assessed the impact of skilled immigration on innovation as measured by U.S. patents per capita. Their empirical investigation finds that immigration could indirectly boost innovation through positive spillovers of inventiveness and entrepreneurship and help achieve critical mass of scientists and engineers in specialized research areas and providing complementary skills in management and entrepreneurship. Other studies of openness point in the same direction; Saxenian (2002) and others (Phelps & Wood, 2006; Saxenian, 2002c; Storper, Farole, & Rodriguez-Pose, 2011; Yeung, 2011) emphasize the critical role of transnational communities in innovation performance. The role of transnational communities and migration for the transfer and building of tacit knowledge has also been investigated by Williams (2007a) and Parrilli (2012). Both stress the importance of the migrant force of skilled human capital as a driver of local entrepreneurial spirit in knowledge-intensive regions, including the Silicon Valley, and suggest that the heterogeneity of social capital is an important factor in enhancing creativity and innovation. Immigrants bring valuable, exploitable tacit knowledge into a region in the form of values, views, and ways of thinking.

Different tacit knowledge bases assure different interpretative schemes of the same external codified knowledge. The diversity of conclusions creates the nutrient means to recombine the knowledge through social interaction, while making it innovative and unique (Broekel & Boschma, 2012). Internationalization and openness may form two complementary forces that are highly valuable to the innovation performance of territories. Our analysis offers a dynamic approach that takes the economic development phase of the IS into account.

Graph 2.1 provides examples of variables and indicators that decrease the cognitive distance of the codified knowledge base to external codified knowledge bases. Such factors improve the absorptive capacity of interacting agents, enable the flow of distant codified knowledge into the country, and increase the stock of codified knowledge. Openness leads to heterogeneous social capital and increase the cognitive distance of tacit knowledge bases available in the country, thereby increasing the innovation potential by novel innovative reconfigurations through mergers. This list is not exhaustive.

Internationalization indicators include outward FDI, research and innovation collaboration, participation in exchange programs, and others. With regard to tacit knowledge, external role refers to openness and, contrary to its relation to internationalization variables, does play a part in increasing the cognitive distance of tacit knowledge bases inside the IS. Inward migration, inward FDI, and tolerance can be indicators that contribute to the increase of heterogeneous tacit knowledge bases, which lead to in an increase of cognitive distance among local agents. Tools that support the exchange of tacit knowledge include vocational training activities, cluster strength, and urban population. A more thorough justification of these indicators is made in the following section.

2.5. Empirical Model

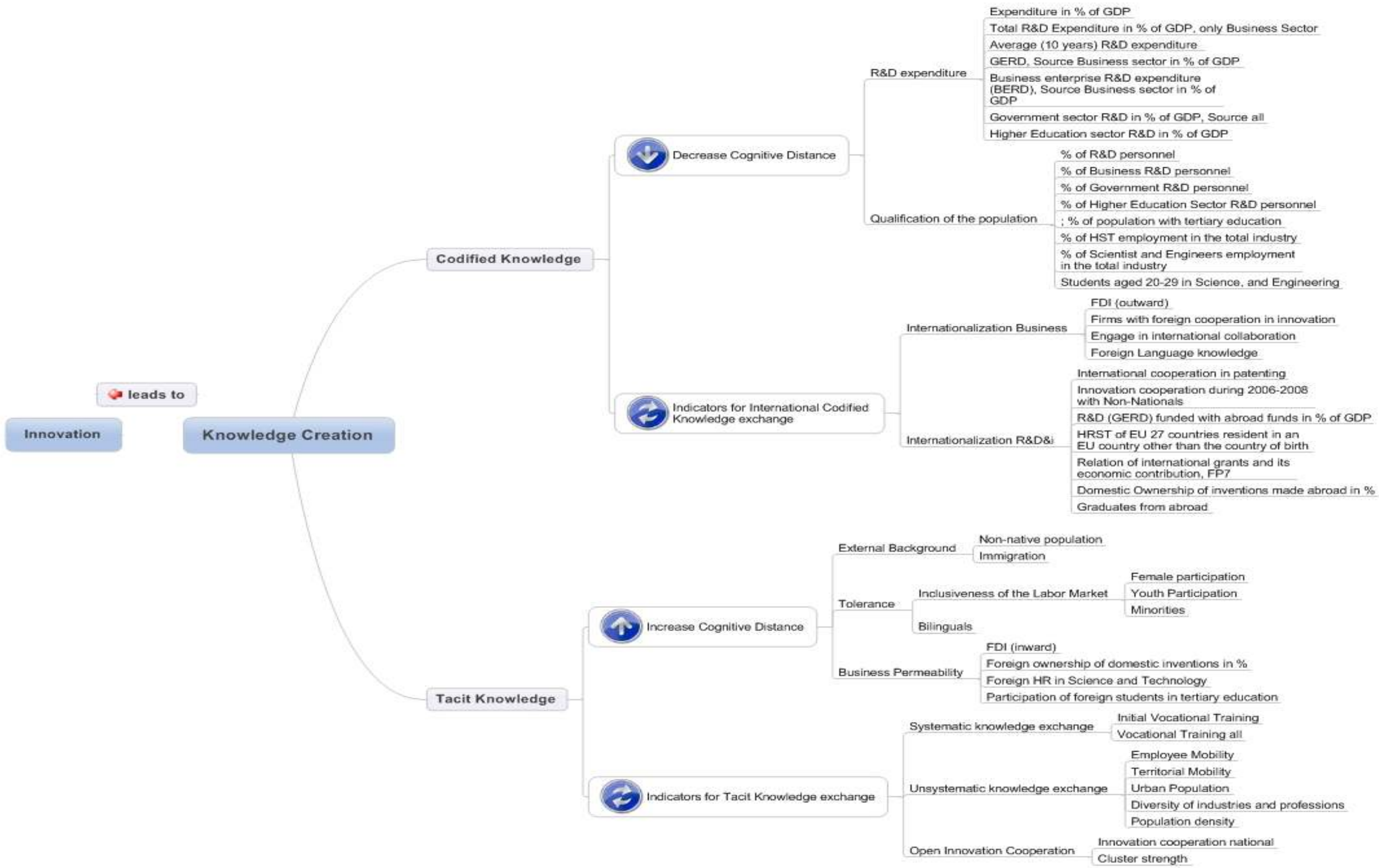
2.5.1. Indicators to Measure Knowledge Creation

The sample used in our first analysis is drawn mostly from 2008 data from the EU-27 member states. Because most data are not available at the regional level (RIS level), we preliminary test the validity of our argument at the National Innovation System (NIS) level. This analysis can be used as reference to engage in further analysis at the RIS level in future case studies or for the analysis of specific indicators (see in this work our chapter four). Graph 2.1 shows possible indicators and their positions in both hypotheses. Knowledge creation leads to higher innovation activity in the IS. In line with our hypothesis, there are two complementary knowledge types: Codified knowledge and tacit knowledge. An increase in the codified knowledge stock has the effect to decrease cognitive distance within the codified knowledge bases vis-à-vis other ISs.

Similarly, tacit knowledge indicators can be classified into two types: those that increase cognitive distance in the IS and those that indicate an exchange of tacit knowledge. Higher heterogeneous tacit knowledge bases increases aggregate cognitive distance in the IS. Therefore, an IS with two groups of people has more cognitive distance than on IS with only one homogenous group. It refers to the number of different groups of society active in the IS. It does not mean however, that individuals should be strangers to each other to have a high cognitive distance. The starting point of the model is the typical European country with a lively civil society. Both types, exchange of tacit knowledge and increase of tacit knowledge augment the stock in the IS. It is important to stress that although cognitive distance in relation to codified knowledge is regarded as the cognitive distance of codified knowledge inside the IS vis-a-vis the stock available in other ISs, cognitive distance in relation to tacit knowledge is regarded as the distance between the individuals inside the same IS.

Codified knowledge, unlike tacit knowledge, can be exchanged both inside and outside the IS, whereas tacit knowledge (due to its characteristics) can mostly be exchanged within a bounded territory. Due to problems of availability, Figure 2.1 contains more indicators than we are actually able to use. Table 2.1 shows only the indicators that have been used in this analysis.

Figure 2.1: Knowledge, Cognitive Distance and Possible Indicators, Factors that Support its Exchange



Source: own elaboration, archive.

In line with our hypotheses, tendencies and relationships at the RIS level should be stronger than at the national level (NIS), as a result of the regionalization aspect of the economy (due to the increasing importance of the tacit knowledge base at that level). Far more tacit knowledge can be transferred at regional levels than at national levels. Therefore, a relationship that can be observed at the national level should be a very strong indicator that it is particularly valid at the regional level. Variables have been selected according to the theory outlined above and are summarized in Table 3.1.

Table 2.1: Knowledge and Innovation Indicators and Variables

#	*Organized as Inputs and Outputs in the Innovation Process* Tacit knowledge		Codified knowledge		Innovation output		Control Variables
	Indicators (Variables) Value and Exchange	Indicators (Variables) of Tacit Knowledge Increasing Cognitive Distance: **Openness**	Indicators (Variables) of Codified Knowledge Reducing Cognitive Distance to Other NIS	Indicators (Variables) Value and Exchange – **Internationalization**	Exploit- type indicators (Variables)	Explore-type indicators (Variables)	
1	**Systematic knowledge exchange** (Initial Vocational Training in companies; Any Vocational Training in companies;)	**External background** (2nd generation persons with foreign background in %, 2nd generation persons with mixed background in %; 1st generation stock of persons with foreign background; Average annual immigration 2000-2010 in % of total population; % of persons with non-native background; % of foreign-born population)	**R&D** (Expenditure in % of GDP; Total R&D Expenditure in % of GDP, only Business Sector; Average (10 years) R&D expenditure (GERD), all sectors in % of GDP, GERD, all sectors in € p.c., 2008; GERD, Source Business sector in % of GDP, 2008; Business enterprise R&D expenditure (BERD), Source Business sector in % of GDP, 2008; Government sector R&D in % of GDP, Source all, 2008; Higher Education sector R&D in % of GDP, Source all, 2008)	**Internationalization Business** (FDI-outward, Firms with foreign cooperation in innovation)	**Business results** (Real labor productivity per hour worked; -% of employment in high-tech sectors, 2008 (Eurostat); Exports of high technology products as a share of total exports; Imports of high technology products as a share of total imports; Trade Deficit / Surplus of high technology products in %; Employment in knowledge intensive activities in %)	**Patents & Public.** (Total Patents Applications; High Tech Patents Applications; Patent Applications submitted by Business sector in %; Patent Applications submitted by Government sector in %; Patent Applications submitted by Higher Education sector in %; Patent Applications submitted by Private Non Profit sector in %; Patent Applications submitted by Individuals in %; Nanotech Patent Applications submitted in %; Biotech Patent Applications submitted in %; ICT Patent Applications submitted in %;Publications)	% of GDP of industry activity
2	**Unsystematic knowledge exchange** (Population density; % of population living in urban regions)	**Inclusiveness** (% difference of employment rate difference of native and foreign born; % difference of unemployed between 2nd generation foreign descent and native; % difference of unemployed of foreign-born and persons born in the	**Qualification of the population** (% of R&D personnel; % of Business R&D personnel; % of Government R&D personnel; % of Higher Education Sector R&D personnel; % of population with tertiary education; % of HST employment in the total	**Internationalization R&D&I** (International cooperation in patenting; Innovation cooperation during 2006-2008 with Non-Nationals; Foreign Language knowledge; R&D (GERD) funded with abroad funds in % of GDP; HRST of EU 27	**Business Innovation** (Enterprises with Innovation Activity in %; Turnover from innovation as the ratio of turnover from products new to the enterprise and new to the market as a % of total turnover; Enterprises with technological innovation in %;	**Market for complementary services** (Venture capital market)	% of large companies

		country; % difference of over-qualification rate of foreign- born and in country-born; % difference of poverty rates of foreign-born and in country- born; % difference of tertiary education rates of 2nd generation migrants and native; Bilinguals)	industry; % of Scientists and Engineers employment in the total industry; Students aged 20-29 in Science, and Engineering)	countries resident in an EU country other than the country of birth; Relation of international grants and its economic contribution, FP7; Participation of foreign students in tertiary education, Foreign ownership of domestic inventions in %; Domestic Ownership of inventions made abroad in %; Foreign Ownership of Domestic Inventions; Graduates from abroad)	Enterprises with non-technological innovation in %; Enterprises with Novel Product Innovations; Enterprises with Novel Process Innovations; % of enterprises implementing new business practices; % of enterprises with new methods of organizing work responsibilities and decision making; % of enterprises implementing new methods of organizing external relations)		
3	**Open Innovation Cooperation** (Innovation Cooperation at national scope by companies with innovation activities; All cooperation activities at national scope by companies with innovation activities; State of Cluster Development;)	**Business permeability** (FDI--inward, Number (thousands) and share (%) of foreign-born HR in Science and Technology Core; Share in % of foreign born HR in Science and Technology)					% of population with more than 65 years

Source: own elaboration, archive.

First, tacit knowledge indicators that relate to an increase of cognitive distance of the tacit knowledge base in the territory can be of external background, based on the capacity to attract and accept non-indigenous people in the IS and its inclusiveness, or related to business permeability. Indicators include *immigration* from outside the NIS, *non-native population*, and tolerance indicators in the form of *inclusiveness of the labor market*. If a large group of a population is discriminated against, does not participate in the labor market, or is linked to a specific business only, the NIS does not take full advantage of the tacit knowledge available in the country.

An inclusive labor market therefore increases the cognitive distance of the tacit knowledge base inside the NIS. For instance, until recently *female participation* in the labor market was rather low and in most countries even today it is lower than male participation. Therefore, tacit knowledge available is used in a suboptimal way, because a group that can contribute through their different experiences and points of view are excluded from the participation process. The same situation applies to minorities who do not participate in the labor market, or are closely linked to specific duties, and to young people who face high unemployment rates due to restrictions or rigidities in the labor market.

Moreover, *bilingual* territories may increase cognitive distance because languages determine ways of thinking. Countries with bilingual communities should have a richer and more diverse tacit knowledge base. Other indicators for tacit knowledge exchange are *foreign ownership of domestic inventions* and *inward foreign direct investment*; they bring tacit knowledge such as different management styles into the NIS. The indicators of *participation of foreign students in the tertiary education system* and *foreign HR in the science and technology system*, for instance through exchange programs, are also forms of engagement in unsystematic knowledge exchanges that circulate codified but also tacit knowledge. Saxenian (Saxenian, 2002a) observed that high-skilled migrants form networks of ethnic communities also with low skilled compatriots and how these networks benefit the host country with knowledge, skills, and capital leading to entrepreneurship.

Second, there are activities that facilitate the exchange of tacit knowledge. Indicators providing this information can be organized into *systematic knowledge exchange*, *unsystematic knowledge exchange*, and *open innovation cooperation*. Indicators that fall under systematic knowledge exchange include *initial vocational training* and other types of vocational training. These forms of training, in which hands-on-experience accumulated in the company is passed on by working together with the apprentice in a systematic way, is a way of learning and putting together the tacit knowledge bases of the individuals and the companies involved. *Vocational training* is an indicator that provides information about the degree of systematization of the transfer of tacit knowledge in the RIS. As Jensen et al (2007) notes, the DUI-mode (doing, using, interacting – based innovation) of innovation, which refers to an experience-based mode of learning, assigns a major role in mobilizing tacit knowledge for problem solving and learning through informal communication and communities of practice. The DUI-mode is knowledge that is rooted in experience and refers to the 'know-how' and 'know-who' types of knowledge that are learned in apprenticeship-relations where the apprentice follows the master, studies both the master's body language and spoken language, and relies upon the master's authority (M. Polanyi, 1958).

There are further non-systematic indicators of tacit knowledge exchanges, such as *employee mobility*. National Innovation Systems with flexible labor markets show higher employee mobility (e.g., Denmark). It is not uncommon to change jobs and industrial sectors. Frequent change of jobs is an excellent indicator for a rich tacit knowledge base, since employees take their knowledge from firm to firm, and from sector to sector (P. Maskell, Bathelt, & Malmberg, 2006). The presence of *diversified professions and industries*, *territorial mobility*, *urban population*, and *population density* are also non-systematic knowledge exchange indicators. Cities enable frequent face-to-face contact and transfer of tacit knowledge bases Arundel and Geuna (2001) and Carlino (2001) have also shown there are important links between economic growth and concentration of people; high concentration of people and firms in cities create an environment in which ideas move quickly from person to person and firm to firm. Parrilli (2012) also notes that frequency and intensity of interactions are important factors in the activation of tacit knowledge.

Third, another form of tacit knowledge exchange is the open innovation cooperation scheme, to enable tacit knowledge exchange. Indicators of such schemes include *national innovation cooperation* figures and *cluster strength* indices. The boundaries of indicators that increase cognitive distance and exchange tacit knowledge are often fluid, especially for non-systematic knowledge exchanges.

In our analysis, codified and tacit knowledge indicators are innovation inputs correlated to innovation outputs in NIS and EU members. Data relates to the year 2008 and available indicators are listed in Table 1 below. Innovation outputs are divided into outputs from exploitation activities, and outputs from exploration activities (Gilsing & Nooteboom, 2006). Exploitation indicators include those related to actual achieved results in business and those related to innovation in products and services. Exploration results relate to radically new knowledge; their indicators are patents and publications, as well as markets for complementary services related to these radically new ideas.

We use Bathelt (Bathelt, et al., 2004) and the literature on absorptive capacity as our major references when selecting indicators with regard to collaboration with external knowledge sources. Cross referencing with external authors provides an indication of the degree of collaboration with external entities (Steinmueller, 2000). Other indicators include available resources to access external knowledge, for instance, knowledge of most commonly used languages in the world. Further, many authors that analyse global knowledge flows and in the international business literature field have used a number of variables that could be summarized under international operations. Foreign subsidiaries or outward FDI are regarded as means for transferring codified knowledge from one IS to another IS. Motivations of firms to engage in these operations include the exploitation and transfer of the firms' resources or to access resources in form of knowledge. The latter could involve also tacit knowledge, though codified knowledge transfers prevail.

Denmark´s labor market is frequently cited as a market that facilitates knowledge exchange and specializes in the DUI mode of innovation (Jensen et al, 2007). Internal migration or census turnover is a similar indicator (VAN DIJK, 2000). Measures of tolerance and diversity could provide us with information on the ability of the IS to take into account different tacit knowledge bases and incorporate them into economic activity. Frequently, although diversity exists, society is unable to take advantage of it. Strong extra-community networks ("bridges") are needed to transfer the tacit knowledge within the country (Woolcock & Narayan, 2000). Discrimination against minorities is an example.

Both *cluster strength* indices and *vocational training* are indicators that measure the degree of systematic tacit knowledge exchange in a territory. Cluster strength is the outcome of an executive opinion survey and provides information on the infrastructure available to enable its exchange and executive usage (Clusterobservatory, 2011). Various firms congregate to collaborate in business activities. Vocational training is an important indicator because such training transfers tacit knowledge from the master to the apprentice (Nonaka, 1991). In countries with powerful vocational training schemes, for instance Germany, tacit knowledge (i.e. on-the-job training) is complemented by classroom education schemes that are representative of codified knowledge.

As previously noted, a key element of tacit knowledge is that innovation performance can be improved by merging two heterogeneous knowledge bases (i.e., tacit knowledge bases) with high cognitive distance (Broekel & Boschma, 2012; Nooteboom, 2007). Immigrants are potential instruments for increasing cognitive distance in an IS. They integrate different values, views, and ways of acting. For instance, Saxenian (2002b) among others, shows how immigration boosts entrepreneurship in the IS. Immigration introduces new tacit knowledge bases (Yeung, 2011) that may lead to new observations and conclusions and facilitate exchanges that produce innovations.

Bilingualism has been identified as an important resource for increasing cognitive distance. As Bialystok observed based on empirical studies, individuals who actively use two languages evolve differently than monolinguals, with bilinguals showing superior cognitive performance (BIALYSTOCK, 2011).

Inward FDI indicates possible spillovers of tacit knowledge at the local level. Tacit knowledge that is external to the IS increases cognitive distance. Keller (Keller, 2001) identifies international trade and FDI as the major channels for technology diffusion across countries; international economic activities lead to additional contacts with foreigners who may possess advanced technological knowledge (exporters, importers, engineers, researchers). This may stimulate the diffusion of (non-codified) foreign technologies. Nevertheless, some risks exist in that inward FDI may generate multicollineality problems as it also conveys codified knowledge inputs (e.g. patents).

Cohen and Levinthal (1990) indicate these spillovers depend on the absorptive capacity of the region. In our analysis, we differentiate innovation output based on Nooteboom's (2000) approach. Output derives from exploitation or exploration activities, with exploitation activities being the process in which a variety of contents consolidates into a dominant design. Exploration activities are experiments conducted with novel elements adopted from a novel context. They entail radical reconfiguration of old systems of exploitation, with tacit knowledge playing a more important role.

Indicators that indicate innovation output from exploitation activities are *productivity* and *productivity growth, new-to-the-firm products,* and *enterprises with product and process innovations.* In manufacturing industries, exploitation activities indicate a shift from product to process innovations, typically leading to a productivity increase.

As competition shifts to efficient production and distribution and new entrants exert further pressure on price, scale division of labor and specialization emerge. Product variety decreases, resulting in minor product adaptations and process improvements. These tendencies can be captured by new-to-the firm products and processes. Products are introduced mainly for differentiation; new processes indicate specialization and increased competition. Variables that indicate innovation output from exploration activities are publications and patents, and market for venture capital.

According to Gilsing and Nooteboom (Gilsing & Nooteboom, 2006), exploration activities are experimentations with new elements, in which existing basic design principles are increasingly questioned. Patents and publications are signals for these activities because every patent and most publications tend to introduce new elements to the science base. Availability of venture capital indicates that there is a market to finance new company ventures to introduce radically new products. Innovation outputs from exploration activities are novel combinations that entail radical reconfigurations of old systems of exploitation; they can be introduced both by established companies and newly-created firms. The next section will explore the relationship of these indicators presented here.

2.5.2.Exploring the Relationship between Openness, Internationalization and Innovation

To explore the relationship between openness, internationalization and innovation indicators have been selected taking into account their meaning as described in the previous section.

A total of 53 input variables (23 that measure openness and 31 that measure internationalization) and 28 output variables, and three control variables add up to 84 x 84 = 7056 correlations and 84 variables. There are n = 27 observations representing the 27 EU member states in 2008.[5] Therefore, *n* observations of *p* variables can be displayed.

The sample correlation coefficient together with its graphical illustrations provides us with initial information on relationships in the data sample. The sample correlation coefficient provides us with information on the relationship between the input data and the output data.

Formula 2.1: Calculation of the Correlation Coefficients

Formula 1: Correlation coefficient between variable *j* and variable *k* is $r_{j,k}$

$$r_{j,k} = \frac{\sum_{i=1}^{n}(X_{j,i} - X_{mean_i})(X_{j,k} - X_{mean_k})}{\sqrt{\sum_{j=1}^{n}(X_{j,i} - X_{mean_i})^2}\sqrt{\sum_{j=1}^{n}(X_{j,k} - X_{mean_k})^2}},$$

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[5] Croatia, the latest country to join the European Union, has not been included in the sample because it was not a member when the data was collected.

The correlation coefficient, r, ranges from −1 to 1. If the r-value is close to −1, the relationship is considered anti-correlated, or has a negative slope. If the value is close to 1, the relationship is considered correlated, or has a positive slope. As the r-value deviates from either of these values and approaches zero, the points are considered to be less correlated and are eventually uncorrelated when the value is zero.

To test the validity of the correlations, we can use the p-value, which is the probability of obtaining a result that confirms the null hypothesis that r equals zero. The lower the value, the less likely the null hypothesis is true and the higher the probability we will reject it.

To calculate the p-value, we first calculate the z-score and then look up its corresponding p-value using the standard normal table. The z-scores assume the sampling distribution of the test statistic to be normal and transform the sampling distribution into a standard normal distribution; Z is expressed in terms of the number of standard deviations from the mean value.

Formula 2.2: Calculation of Z-score

Formula 2: Z value

$$Z = \frac{X - \mu}{\sigma}$$

Where X being the experimental value, μ the mean and σ the standard deviation

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A result is deemed statistically significant if it is unlikely to have occurred by chance. Popular levels of significance are 10% (0.1), 5% (0.05), 1% (0.01), 0.5% (0.005), and 0.1% (0.001).

Table 2.2: Overview of Correlations: Openness and Internationalization with Innovation Output Variables

	O1_Producty	O1_InnoAc	O1_InnTurn	O1_InnoTech	O1_Innonotech	O1_NovProd	O1_NovProc	O1_HighEm	O1_HighExp	O1_HighIm	O1_HighTrade	O1_EmpKnow	O1_NewPrac	O1_NewResp	O1_NewRelex	O13_Em_High	O2_Pat	O2_HiPat	O2_BusPat	O2_GovPat	O2_EduPat	O2_PNPPat	O2_IdvPat	O2_NanoPat	O2_BioPat	O2_ICTPat	O2_VC	O23_Publ	
OPENNESS																													I2_Frg2nd
			-0,58																										I2_Mixed
	0,67											0,73											0,63				0,58		I2_For1
	0,60								0,64	0,56	0,57	0,72											0,54						I2_Immpy
	-0,52											-0,52						-0,58	-0,52							-0,59			I2_Native
												0,53											0,63				0,52		I2_Forborn
	0,56																0,66	0,65	0,64					0,53	0,70	0,64		0,65	2_Difemp
																													I2_Intg2
	0,77					0,52						0,70					0,74	0,56	0,72				0,54	0,51	0,67	0,62	0,76	0,67	I2_Intg1
																													I2_Qua
	0,68											0,59					0,66	0,60	0,66				0,53		0,51	0,63	0,53	0,61	I2_Pove
																													I2_TerE2
												0,52																	I2_FDI_in
INTERNATIONALIZATION	0,79											0,82					0,50		0,53				0,50				0,78		I41_FDI out
																													I42_Co-Pat
														0,53															I43_In_Col
										-0,50																			I4_Lang
	0,61																0,67	0,65	0,63				0,57		0,62	0,65		0,71	I4_RDExt
																													I4_ForHRST
																													I4_FP7
	0,58											0,71											0,59				0,76		I4_ForHRSTC
																													I4_ForStu
																	-0,51												I4_ForOwnIn
									0,76	0,62	0,71	0,68																	I4_DomOwn
																													I4_PatFor
																													I4_GradFor
																													I4_Stuout
									0,76		0,88																		I4_AirPa
	O1_Producty	O1_InnoAc	O1_InnTurn	O1_InnoTech	O1_Innonotech	O1_NovProd	O1_NovProc	O1_HighEm	O1_HighExp	O1_HighIm	O1_HighTrade	O1_EmpKnow	O1_NewPrac	O1_NewResp	O1_NewRelex	O13_Em_High	O2_Pat	O2_HiPat	O2_BusPat	O2_GovPat	O2_EduPat	O2_PNPPat	O2_IdvPat	O2_NanoPat	O2_BioPat	O2_ICTPat	O2_VC	O23_Publ	

29/05/2012, own elaboration, archive.

If a test of significance gives a p-value lower than the significance level chosen, the null hypothesis is rejected. Choosing the level of significance is a somewhat arbitrary task, but for many applications, a level of 5% is chosen because it is conventional to this analysis. Hence, 5% has been chosen in the present study. The correlation results that are significant are presented in Table 2.2.[6]

Our first analysis of all input variables with an external component (i.e. input variables that indicate 'openness') and variables that indicate internationalization, displayed in Table 2.2., show that after applying a filter for significant correlation and significance, tacit knowledge components with a positive and significant correlation are more numerous than codified knowledge components.[7]

As we expected, highly correlated values with very low significance values are observed between the tacit knowledge dimension *value and exchange* (systematic and unsystematic knowledge exchange, open innovation cooperation) and the output variables, as well as between the codified knowledge dimension with the objective of reducing cognitive distance *(R&D* and *qualification of the population*) and the output variables. Particularly high values are observed for *initial vocational training*, *all vocational training* activities with *productivity* (0.68, 0.66)[8]. In addition, high *clustering* and *productivity* show even higher values (0.82). Furthermore, *clusterization* seems to be correlated with *employment in knowledge intensive industries*. Moreover, exploration activities also seem to benefit from clusterization, showing correlation values of 0.79 and 0.70 in the case of *high technology patents*. *Publications* are also positively correlated with *clusterization*, with a value of 0.73.

With regard to codified knowledge variables that reduce cognitive distance and innovation output variables, positive correlations can be observed for total *R&D investment* and *productivity* (0.88), *R&D and patents* (0.91) and *R&D and high technology patents* (0.80). Further, *R&D, human resources in science and technology* and *percentage of scientists and engineers, scientist and technical personnel*, are both highly correlated with exploitation activities, including *productivity and employment in knowledge intensive industries*, and exploration activities including *patents, high technology patents, venture capital investment,* and *publications*. All control variables are insignificant. Table 2.3. summarizes the most important relations with respect to the external dimension. Within the tacit knowledge sphere,

[6] The complete table can be find in the annex.
[7] Attention is called only to the number of available values at the grey zone and at the light blue zone; the meaning of the variables is not important at this stage.
[8] Productivity measured in real labor productivity per hour worked, € per hour worked, Eurostat.

the presence of *non-native inhabitants* in a territory has a positive correlation with *productivity* (0.57), *employment in knowledge intensive industries* (i.e. exploitation output) (0.67) and, to a lesser extent, with outputs of exploration type with *patents* (0.33) and *venture capital* (0.53). *Foreign born human resources in science and technology* show particularly high values for *venture capital investment*.

With regard to codified knowledge, selected variables include *outward FDI, co-patenting, innovation collaboration, R&D* in the country financed with external sources, participation in *EU research programs (FP7)*, and *domestic owned foreign inventions*. Here, results are less clear, with positive correlations between *outward FDI and productivity* (0.79) and *outward FDI* and *employment in knowledge intensive industries* (exploitation output). *Outward FDI* also shows positive correlations to *patents, venture capital investment, and publications*. *Co-patenting* and *innovation collaboration with foreign entities* do not show any positive correlation with any output variable; *R&D financed with external sources* is correlated to *productivity* per hour worked and *patenting* in particular, and *domestic owned foreign inventions* is correlated with *productivity* per hour worked and *high tech exports*.

By analyzing selected values, we observe the strong correlation with a few outliers of *non-native population* and *productivity* (Figure 2.2). Estonia and Latvia show a high percentage of non-native population and low productivity per hour worked; Denmark and Finland, with a lower percentage of non-native population, show higher productivity values than their non-native value would suggest.[9]

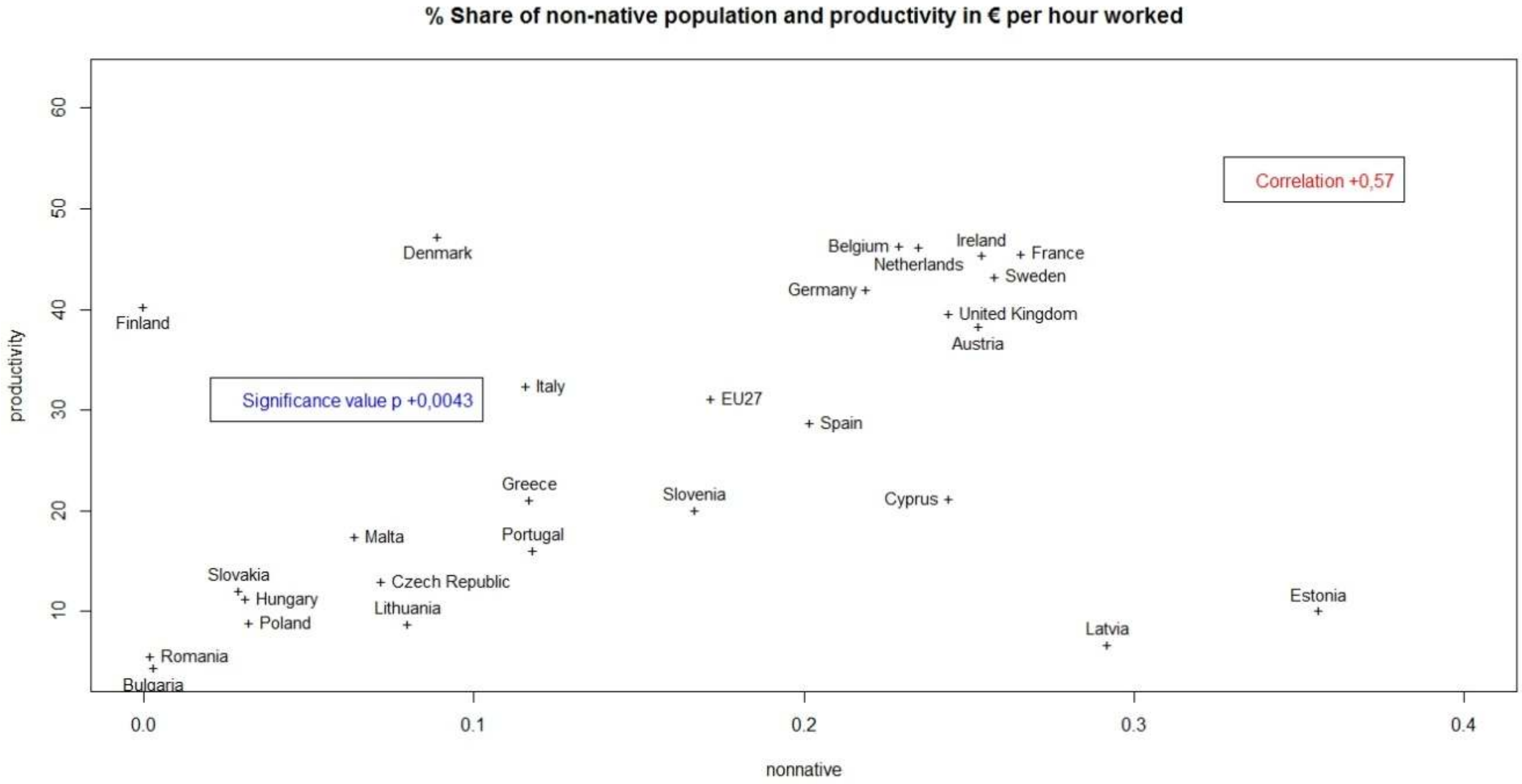
[9] As a result of the break-up of the Soviet Union, Estonia and Latvia have a very high percentage of Russian descendent population that is not naturalized. The Scandinavian countries are outliers at the other end. Finland and Denmark might compensate the lower value of non-native population and share of foreign HR in science and technology respectively (Finland) with other variables that increase cognitive distance of the tacit knowledge base (or instance, Denmark's high labor mobility or Finland's inclusive education system). Labor mobility increases cognitive distance as tacit knowledge bases from other companies and industries are shared. Inclusive educational system has a similar effect. Inclusiveness results in heterogeneous classrooms that increase coordination costs but increase cognitive distance.

Table 2.3: Correlation of Input Variables with an External Dimension and Output. Bold Values Show Significance, p < 5 %

O1_Productivity	O1_High Tech Exports	O1_Employ know. ind.	O2_Patenting	O2_Hightech Patenting	O2_Venture Capital	O23_Publications	
0,57	0,32	***0,67***	***0,33***	***0,11***	***0,53***	0,07	**I2_Non-Native**
0,58	***0,43***	***0,71***	0,32	0,08	***0,76***	0,19	**I2_Foreign HRST**
0,79	***0,39***	***0,82***	***0,50***	0,36	***0,78***	***0,44***	**I4_FDI outward**
0,01	-0,01	-0,02	-0,13	-0,19	0,18	0,04	**I4_Co-Patenting**
-0,25	-0,06	-0,24	-0,25	-0,13	-0,33	-0,24	**I4_Innovation Collaboration**
0,61	0,11	***0,48***	***0,67***	***0,65***	0,35	***0,71***	**I4_R&D financed abroad**
0,29	0,08	0,26	0,36	***0,48***	0,12	***0,40***	**I4_FP7 participation**
0,50	***0,76***	***0,68***	0,25	0,19	***0,43***	0,14	**I4_Dom. owned foreign inventions**

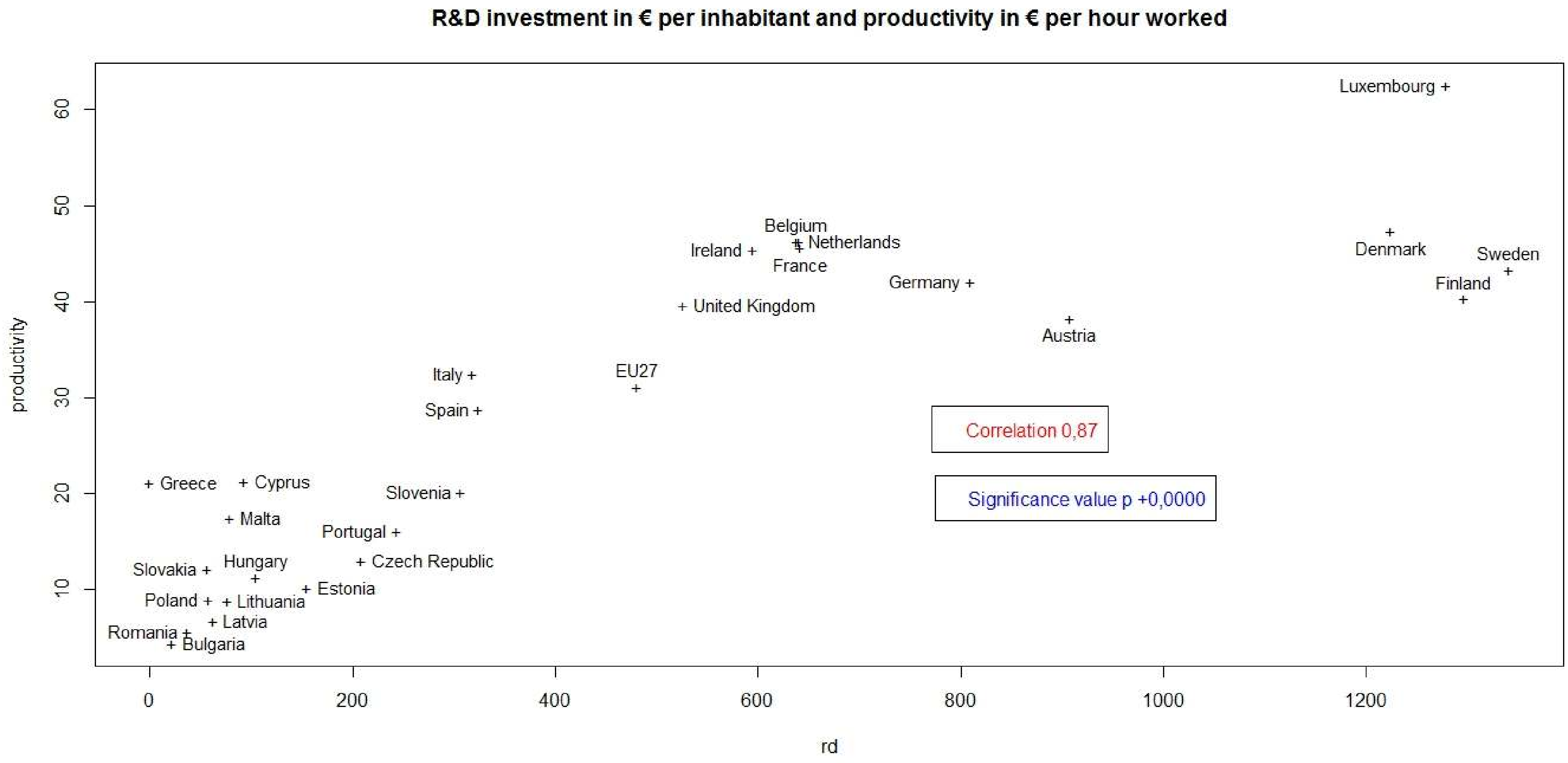
Source: own elaboration, archive.

Figure 2.2: Positive Correlation with Finland, Denmark, Latvia and Estonia as Outliers



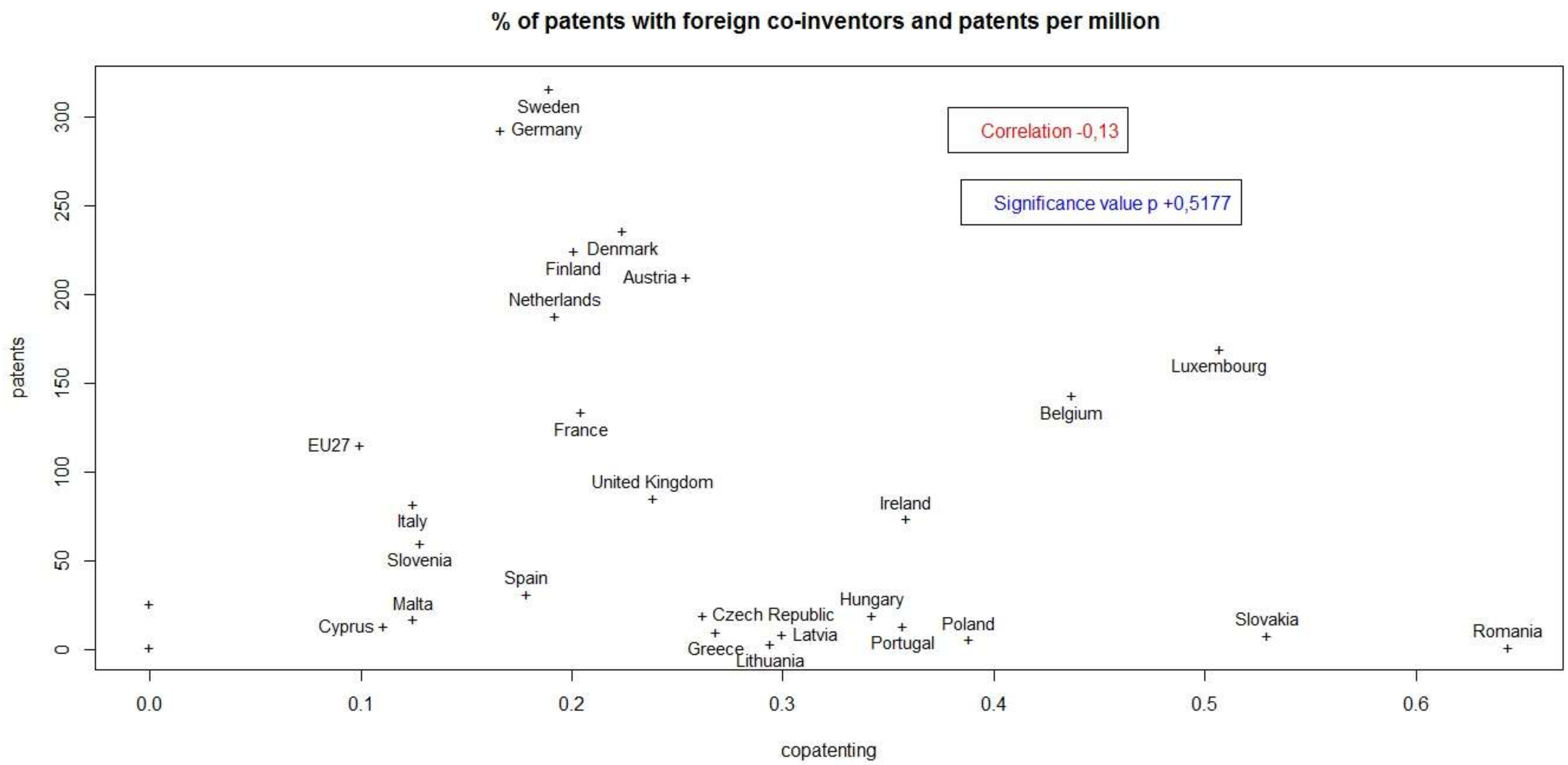
Source: own elaboration, archive.

Figure 2.3: Denmark, Sweden, Finland, Underperforming



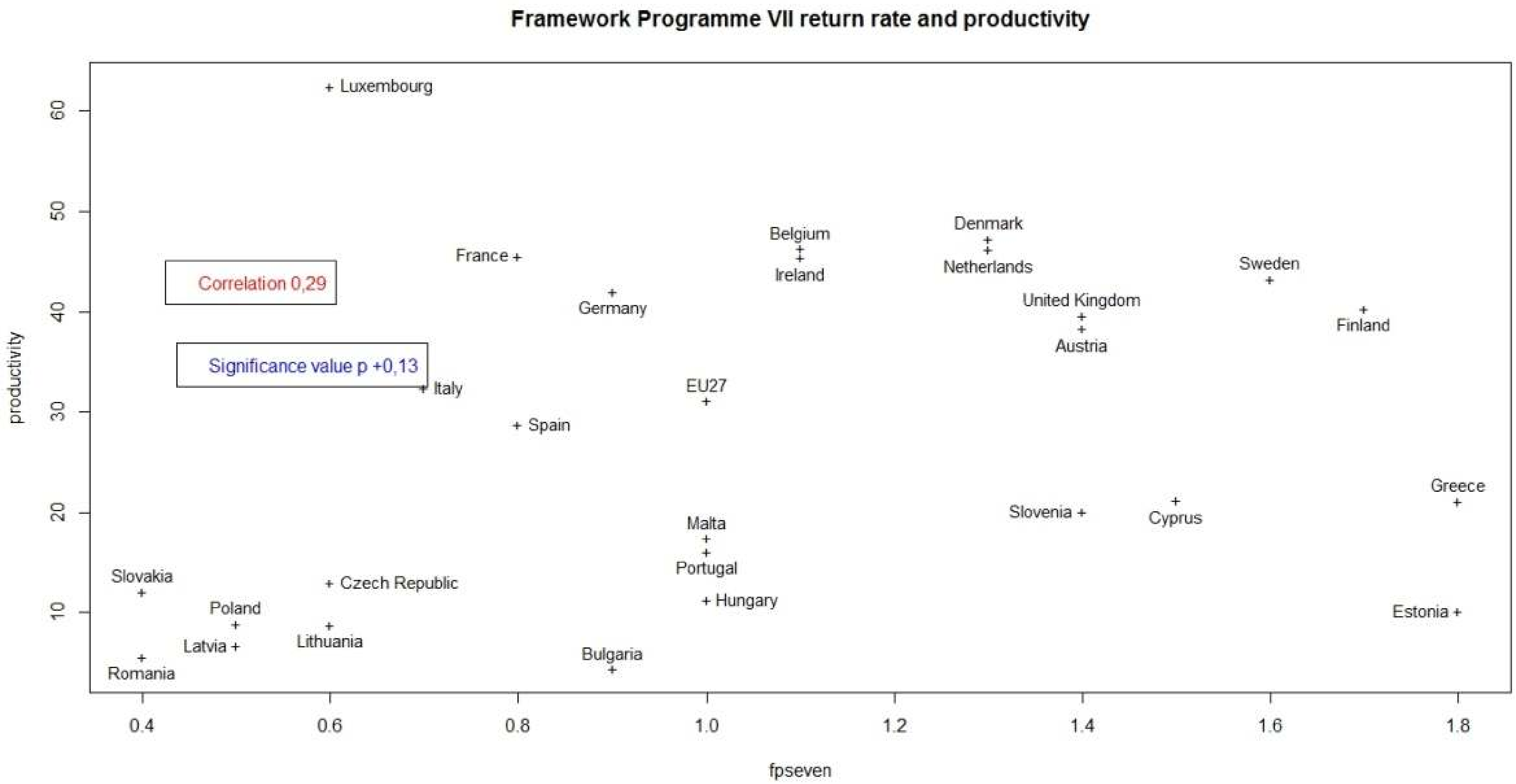
Source: own elaboration, archive.

Figure 2.4: No Correlation Can Be Observed for Exploration Activities; Groups of Countries



Source: own elaboration, archive.

Figure 2.5: No Correlation Can Be Observed With Government-Financed Funds



Source: own elaboration, archive.

Moreover, Finland and Denmark's high productivity per hour worked is a result of the superior effort in investing in R&D, that is (according to our analysis) investment to reduce cognitive distance of the codified knowledge base. It is striking that when *R&D investment* and *productivity* values are analyzed as a ratio, these countries are among those that substantially underperform. Future analysis should investigate how such under-performance is related to the low value of the *non-native population* indicator. The same pattern can be observed when correlating *foreign-born human resources in science and technology* with *employment in knowledge intensive industries*. In particular, Denmark and Finland show low levels of influx of *foreign-born HR in science and technology*. With regard to the value and exchange of codified knowledge (internationalization business and internationalization R&D&I), the results are less clear. Positive correlation can be observed only for outward FDI and the innovation output variables.

In our analysis of codified knowledge exchange of a country with its exterior (i.e. internationalization indicators including *co-patenting*, percentage of *patents with a foreign co-inventor*, and *patents* registered overall, as an output variable), it is of particular interest that no such correlations exist. We observe groups of countries that cluster around similar values. Sweden and Germany show high patent values and moderate co-patenting values. Netherland, Denmark, Finland, and Austria show values that are balanced at a high level; France and the United Kingdom are balanced at a lower level, and there is a group of countries with high co-patenting values and low patent values that includes Portugal, Poland, Czech Republic, Latvia, Greece, and Lithuania.

This observation suggests that sufficient absorptive capacity is needed to take advantage of foreign cooperation and that action on codified or tacit knowledge development depends on development stage. A similar observation can be made with regard to the return rate of European Commission *Framework Programme VII* funds and *productivity rates* in term of € per hour worked: there seems to be no relation between the two variables. A high participation rate in FP7, which refers to the return rate in relation to the contribution to the fund, does not guarantee higher productivity values (per hour worked).

However, there is a positive correlation of R&D activities financed with *foreign capital sources* and *patent* application per million inhabitants. Positive correlations also exist with *domestic owned foreign inventions* and output variables. This suggests that absorptive capacity exists when R&D is financed with foreign capital, which materializes in patent applications. Both indicators, R&D financed with *foreign capital sources* and *domestic owned foreign inventions* indicate codified knowledge transfer of the private sector as a result of internationalization activities.

2.6. Conclusion

This analysis is a first attempt to examine the external role in Innovation Systems. For that purpose, national data in the EU 27 member states have been analyzed and grouped into tacit and codified knowledge components. The external role has been analyzed under the assumption that it is essential to increasing the cognitive distance of the tacit knowledge base (openness) and vital to the value and exchange of the codified knowledge base at the local level (internationalization).

Based on the observations made, we conclude that a relationship exists between the external role and innovation output variables. Moreover, our work proposes a theory to explain direction of causality. Openness variables in general show more convincing results, whereas internationalization figures show strong correlations particularly in fields dominated by private business. *Outward FDI*, *R&D financed with external sources* and *domestic owned foreign inventions* all point towards the strong role of firms in these variables. However, public funds earmarked for R&D&I collaboration, including the *Framework Programme VII, foreign collaboration in patenting*, and *collaboration activities in innovation with foreign sources*, do not show clear results. High-performance countries group themselves together around an optimal value to exchange codified knowledge (internationalization), whereas low performers do not seem to benefit from external codified knowledge flows.

Reduced cognitive distance between the emitter and the receiver may enable the flow of codified knowledge, for instance through the same company in a similar corporate culture or industry sector; this is reflected in our finding of a positive correlation with innovation output variables. This finding suggests RISs must have sufficient absorptive capacity in the form of investments in the codified knowledge base, that is, they must reduce their cognitive distance to the external world through expenditures in R&D and education. However, public funds that provide incentives for transnational collaboration between different companies - including FP VII funds, where we may assume a strong role of public finance - show no correlation. Countries group themselves around an optimal value depending on their economic development stage. No conclusions can be made for low-performing countries, or for innovation outputs of the exploration type. However, exploitation-type variables, which are closer to the market, seem to benefit more from internationalization.

High potential exists for activating and cultivating tacit knowledge bases that increase cognitive distance at the local level. For instance, there are strong roles for *non-native personnel* and *foreign-born human resources in science and technology* and a number of indicators for innovation output results, of both exploitation and exploration types. This finding calls for a successful integration and cultivation of externally-sourced tacit knowledge bases in the country. Countries that show a low percentage of non-native population are underperformers in the relationship between codified knowledge input and innovation output, suggesting that higher output could be achieved through greater openness.

The policy implications of our findings are twofold. Mainstream internationalization policies that deal with the global knowledge flows should be distinguished between openness and internationalization activities. Internationalization policies are effective if emitters and receivers have similar codified knowledge bases in the form of reduced cognitive distance. High performers should have an internationalization policy in place to search for an optimal value. Low performers should tackle the build-up of absorptive capacity to increase their codified knowledge bases and thus reduce cognitive distance to high-performers outside the RIS. All countries should activate and cultivate external tacit knowledge bases at the local level to increase innovation performance. This could be achieved through inclusive institutions allowing pluralism, integration, and collaboration activities of communities with distant cognitive knowledge bases, and by valuing the importance of constant immigration in general. To find optimal values in internationalization, public policies should provide incentives to the private sector to manage the internationalization network themselves or limit internationalization policies to those (internal) R&D groups with unquestionable worldwide excellence. These could be R&D groups that lead through their publications activities research in a specific area and are able to lead international R&D networks.

Our study uses national data; however, we hypothesize that the observed correlation are even stronger at the regional level. Future research is needed to confirm this assumption (we make a more relevant application at the regional level in chapter three and four).

Moreover, our research is applicable only to advanced economies with stable institutions and existing RISs; it disregards extreme cases. For instance, negative effects associated with the increase in the cognitive distance of the tacit knowledge bases are more likely at the local level. Transaction costs as a result of misunderstandings and conflicts increase, and there may be extreme cases in which these costs outweigh the potential innovative outcome from merging two distant tacit knowledge bases. The same can be said for the codified knowledge base. A certain cognitive distance may be needed to justify any collaboration. Our study departs from the typical European case, examining cases of limited migration and high levels of R&D and education standards as compared to other economically developed parts of the world. Therefore, future research must take into account the conditions and the context of each RIS and limit the scope of the analysis.

Our research has provided the foundation to continue with the work by formulating selective hypotheses, selecting appropriate variables, and formulating concrete production functions for the future. Further investigation could determine how the variable ‘migration’ and the variable ‘innovation input’ predict innovation output variables, which could then be compared to the real value. In this way, a formula could be applied to check the interplay of both dependent variables. Similarly, researchers could formulate numerous hypotheses on a range of relationships in various research areas - important steps in determining the importance and validity of the concept.

CHAPTER 3

THE ROLE OF OPENNESS IN THE KNOWLEDGE CREATION PROCESS LEADING TO HIGHER PROPORTIONS OF CULTURAL AND CREATIVE INDUSTRIES IN THE REGIONAL ECONOMY

3. The role of openness in the knowledge creation process leading to higher proportions of creative industries in the regional economy

3.1. Introduction

In a recent article about migration in Europe caused by the southern Euro-area crisis, the German Minister for Employment Ursula von der Leyen (2013) referred to inflows of migrants from southern and eastern European countries as a stroke of luck; the new arrivals, she said, were helping Germany become more creative and international. The Minister's insightful comment raises several questions about the implications of migration in the globalized economy.

In 2001, the importance of creative industries to creativity was acknowledged by the U.K. Department of Culture, Media and Sport (DCMS, 2001); it defined creative industries as "those industries which have their origin in individual creativity, skill and talent and which have a potential for wealth and job creation through the generation and exploitation of intellectual property." This definition recognized that, along with human capital, advertising, architecture, art and antiques, crafts, design, designer fashion, film and video, interactive leisure software, music, performing arts, publishing, software and computer services, television, and radio in the United Kingdom have close economic relationships with other sectors such as tourism, hospitality, museums, galleries, heritage, and sport. The DCMS called for the integration of policies that target creative industries into a regional development strategy, to foster a dynamic business environment, upgrade the talent and skills base, and increase innovation.

The concept of creative industries can be divided into traditional and non-traditional creative enterprises (L. Lazzaretti, Boix, & Capone, 2008). The latter comprise new sectors linked to the digital economy, marketing, design, and logistics. Research on creative industries includes work on creative cities (Jacobs, 1969), a line of research that has become known as creative class literature (Florida, 2002a). Creative class literature interprets the presence of bohemians in a regional environment as a feature that underlies openness to innovation and creativity (Florida, 2002b). Its findings show that bohemians, artists, musicians, and cultural producers correlate strongly with openness indicators such as the percentage of people born abroad and levels of tolerance; they also reveal strong correlations between bohemians and the high technology industry.

Our objective is to investigate the relationship between openness and creativity in Europe's regions, based on these observations. We analyze whether greater openness to global sources of human and social capital leads to greater creativity, and whether the tacit knowledge available in the region through these sources is complementary to the codified knowledge available in the region. We add to empirical evidence by analyzing the relationship through a principal component analysis (PCA); we also include a theoretical analysis of the deep causal links that make the mutual attraction of talent, technology, and tolerance (the "three Ts") (Florida, 2007) so important to the development of creativity (Sacco & Segre, 2009). The insights gained from this theoretical understanding of knowledge creation will strongly benefit practitioners who need to understand the specifics of the setting in which they operate.

Our theoretical analysis is based on the distinction between codified and tacit knowledge, the latter being an essential part of creative industries. Creative industries are based on symbolic knowledge bases (B. T. Asheim & Coenen, 2006), with the objective of creating meaning and desire (Asheim, et al., 2011). It is transmitted by aesthetic symbols, images, (de)signs, artifacts, sounds, and narratives and is often narrowly tied to a deep understanding of habits and norms. With this understanding, we are able to determine some critical conditions for regional development. The case of self-governance of the creative industries in Berlin (see Section 4), characterized by self-organization through "culture-preneurs" and the absence of public administration (Lange, Kalandides, Stöber, & Mieg, 2008), seems to confirm that public policies might not be able to steer a process to become a creative and innovative region. In Section 2, we examine literature on creative industries and the creative economy. In Sections 3 and

4, we outline our theoretical understanding of the role of openness in the knowledge creation process, by providing a brief overview of knowledge types and relating openness to knowledge creation. In Section 5, we present an econometric model that demonstrates how openness variables affect creative occupations, based on a linear regression analysis. The model is constructed with data from European regions at the NUTS-2 level. European and national and regional administrations in Europe regard regions as appropriate geographical entities in which to develop and implement innovation policies; creativity is increasingly acknowledged to be a fundamental precursor to innovation, entrepreneurship, and economic resilience in the regions (Commission, 2006; Cooke & De Propris, 2011; ESPON, 2011). In Section 6, we interpret the results, outline study limitations, and suggest new lines of research.

3.2. Creative Industries

The emergence of Berlin as a creative powerhouse in Europe and in the world provides us with an interesting demonstration case (Davies, 2010). Berlin's creative industries account for 20% of Berlin's gross domestic product. After reunification in 1991, Berlin´s economy stagnated and its population decreased as a result of 150,000 jobs lost in the traditional industries: unemployment rates peaked at 20%. Nevertheless, between 1991 and 2001, Berlin was able to maintain its attractiveness due to its young and international population, overall moderate price levels, and rent-controlled dwellings (Lange, et al., 2008). It succeeded in becoming a magnet for artists, fashion designers, writers, and high profile exhibitors. Creative enterprises from Germany and around the world became aware of its talent pool. In the first decade of the new millennium, companies such as Universal Music, MTV Deutschland, and Popkomm, an international music and entertainment fair, came from other cities in Germany to establish themselves in Berlin (Lange, et al., 2008), By 2013, Berlin was no longer known by the typically German stereotype of having an efficient and organized work ethic (as demonstrated by the difficulties of building a new airport in the city). Instead, it had become a dynamic cluster of startups operating in the new economy (E. Müller, 2013).

The case of Berlin confirms Florida's (2006) theory of the creative class; talent did not follow job opportunities, as the majority of geographers and social scientists proposed (e.g., Lucas, (1988). Instead, companies located in places with a rich base of skilled and creative people. Study of the creative class is one of two main research strands in the literature on creativity. While the creative industry focuses on clusters, enterprises, and their sectors and territories (Bakhshi, McVittie, & Simmie, 2008; DCMS, 2001), the creative class centers on creative cities (Florida, 2002a), acknowledging the human factors that support creativity. Creativity literature recognizes creativity as a resource that generates innovations and assets for overall regional development (Cooke & De Propris, 2011).

The emergence of the literature on creativity in the last decade is a result of the finding that creative industries are strongly related to medium and high-tech manufacturing (De-Miguel-Molina, Hervas-Oliver, Boix, & De-Miguel-Molina, 2012). This finding was confirmed by Chapain et al., (2010), who explored the mechanism of creative industries as potential sources of innovation for knowledge intensive business services (KIBS) and high-tech manufacturing companies, which tend to locate close to one another. Creative industries play a vital role in upgrading existing industries, thanks to their innovation content (Cooke & De Propris, 2011). They become part of a wider Regional Innovation System (RIS) - defined as the systematic interactive learning process of the regional production structure (knowledge exploitation subsystem) and the regional support infrastructure (knowledge exploration subsystem) (Cooke, 2001) - to generate virtuous circles of innovation and growth.

Moreover, creative industries and clusters not only explain innovation performance, but also act as predictors of their sustainability of growth. For instance, in an analysis based on the EUROSTAT Labor Force Survey (2011), ESPON (2008) found that economically successful regions during crisis have high levels of creative workers and that regional economic recovery is powered by a creative workforce.

The literature on the 'creative class' has found a positive relationship between bohemians and high technology (Florida, 2002a). The former attract the latter, when bohemians signal that a place is supportive to talent and therefore open to accept creative approaches. This signaling is conducive to the birth, growth, development, and attraction of new and high- technology industries. In this context, diversity implies low barriers to entry for talent, and talent attracts high technology. Other attraction factors include variety of professions (L. Lazzaretti, et al., 2008), openness (Florida, 2002a), diversification of the economy (Cooke & De Propris, 2011; Jacobs, 1969; Page, 2008), tolerance (Florida, 2007), pluralism (Runge, 2009), internationality (Lange, et al., 2008), and mobility of the workforce (Müller, Rammer, & Trüby, 2009). These factors create the proper climate to attract and develop creative industries and build higher innovation capacity in other sectors of the local economy.

These factors are not the only explanations for innovation capacity of the RIS and economic prosperity. In a critical review of Florida's creative class concept, Donegan et al. (2008) found indicators such as human capital and industry composition performed as well or better than Florida's creative class index (talent, tolerance, and technology) in explaining job and income growth. They maintained that apparent high correlations of the creative class are specific to big cities and dependent on multiple factors that are too complex to understand. They argued the creative class is not a substitute for traditional business development strategies, and suggested public policy makers should focus on education, upgrading of skills of the workforce, and other traditional forms of business promotion.

Thus, human capital and the creative class play different but complementary roles. Florida et al. (2008) offered an explanation based on Page's (2008) view that tolerance enables cognitive diversity and leads to better decision making. The creative class reflects values that are open-minded, meritocratic, tolerant of risk, and oriented to self-realization, all factors that are closely related to entrepreneurial activity and making available local resources more efficient. Florida (2007) referred to the complementary roles of the three Ts in promoting economic growth. For this reason, he called for more research on how factors such as tolerance, diversity, and openness shape the creative class and human capital of a region,

Our research seeks to connect these aspects by segregating knowledge into its codified and tacit parts. Human capital is closely related to codified knowledge stock; openness enables the entrance of new tacit knowledge bases into the RIS. In theory, creative industries, based on symbolic knowledge with high proportions of tacit knowledge, benefit from these new tacit knowledge bases entering the region.

Our hypothesis is based on Asheim and Coenen's (2006) classification of RISs according to knowledge specialization, with varying amounts in codified and tacit knowledge: Analytical knowledge is science-related (largely codified), synthetic knowledge is linked to industrial and engineering (both knowledge types), and symbolic knowledge is associated with the aesthetic attributes of products such as designs, images, or the economic use of cultural artifacts. The authors cite media, advertising, design, and fashion as examples of industries based on symbolic knowledge. These industries are highly context-specific and require large amounts of tacit knowledge dedicated to creating and exchanging new ideas. By segregating knowledge into codified and tacit parts and connecting each part to employment in the creative industries, we are able to explain the complementary role of the factors identified by literature on the 'creative class'. In the next chapter, we examine the knowledge creation process and the role that openness plays in developing tacit knowledge.

3.3. Knowledge Types

Polanyi (1966) distinguished between tacit and codified parts of knowledge, by describing tacit knowledge as that embodied in innovators and accumulated through experience, and codified knowledge as that which is written down. The process of acquiring tacit knowledge is equivalent to the process by which human beings orient themselves in an unknown territory and make sense of the world by interiorizing details of phenomena in the subconscious. People know more than they are able to put on paper. Polanyi argued that tacit knowledge is shared when people jointly create a social environment and when they assist one another in discovering new things and solving new problems. Tacit knowledge, in other words, is based on human capacities that appear to be accessed without the intermediation of any formal code (Cowan et al, 2000). Consequently, tacit knowledge is held in forms that are transmitted by working or learning together, for example from master to apprentice (Perraton & Tarrant, 2007).

An example of the importance of tacit knowledge in research activities is the cultivation of blue-fin tuna in fish farms. The strong demand for this fish has led to decreasing stock and record prices. Researchers at the University of Kinki in Osaka, Japan have been working for 40 years to breed the Pacific blue-fin tuna. They have succeeded in commercializing Kindai, a fishfarm tuna variety that now provides considerable income to their university. Despite this financial incentive, European researchers had not succeeded in raising the Atlantic variety in similar terms. In an attempt to close the knowledge gap, researchers at the Spanish Oceanographic Institute (IEO) in Murcia on the Mediterranean coast hired Manabu Seoka, Professor of Aquaculture at the University of Kinki.

After years of raising blue-fin tuna in tanks, the professor had developed a feel for critical times in the process of raising the fingerlings. He closely monitored them, day and night, and adjusted oxygen, artificial light, and food in a delicate and changing balance. It was only by working together with this expert that the IEO succeeded in raising twenty Atlantic blue-fin tuna in fish farms, resulting in the biggest such achievement in Europe to date (Sentker, 2013). This example shows tacit knowledge has a slow diffusion process, whereas codified knowledge - knowledge that has been written down—can travel large distances and be remotely accessed by others. To clarify both concepts in more detail, Lundvall et al. (2002) defined tacit knowledge as the social ability to communicate and co-operate with different kinds of people (know-who) and the ability to do something (know-how)—the ability to actually transform knowledge and use it in practice. Codified knowledge is based on facts (know-what) and laws in motion in nature (know-why). Know-what and know-why may be obtained through reading books, attending lectures, and accessing data bases, but the other two categories are rooted in practical experience and only partly codifiable. These knowledge types are typically developed and kept within the borders of an individual firm.

Along with RIS literature, literature on tacit knowledge has been growing in relevance due to the lower mobility of theis knowledge. Because codified knowledge, defined as knowledge that has been articulated (Cohen et al, 2000) is more easily accessed, it has greater global mobility and availability; therefore, tacit knowledge is the differential that makes companies and regions gain a competitive advantage (John Kay, 1999). This effect is caused by the complementary application of both knowledge types and the fact that tacit knowledge, in contrast to codified knowledge, can be excluded: learning is more costly than the acquisition of codified knowledge (Coe et al, 2004; Cohen et al, 2000; Haruyama, 2009; Jensen et al, 2007; I. Nonaka & Takeuchi, 1994; Parrilli et al, 2010; Michael Polanyi, 1966). The greater the intensity of knowledge in the regional economy, the higher the stock of codified knowledge and the more specialized its tacit knowledge base, resulting in a RIS able to distinguish itself through constant innovation.

The uniqueness of an RIS is based on its tacit knowledge rather than its stock of codified knowledge accumulated over time. Moreover, the proportions of codified and tacit knowledge may vary depending on the benefits and costs of codifiable, but tacitly held, knowledge, Tacit knowledge includes non-codifiable and non-codified knowledge (Cowan et al, 2000); the latter can be kept that way intentionally, to hold knowledge within the boundary of a firm, or simply because there has not been enough time to codify it. An example is the IT sector in Silicon Valley, where technology is changing rapidly. Both knowledge types imply competitiveness through stickiness of knowledge in the company or region. Thus, relying excessively on codified knowledge makes the company or region vulnerable to competitors and innovation capacity. Unless strategic intellectual property rights (IPRs) are set in place, knowledge can travel easily through space and an RIS may quickly lose its innovation leadership in an industry.

Another problem of excess codification is that it “can become a source of ‘lock in’ to obsolete conceptual schemes” [(Cowan et al, 2000): 248], with adverse effects on creativity and change; codified knowledge persists on the basis of what has been done in the past. Econometric studies confirm that activities with large proportions of tacit knowledge tend to concentrate in sectors (Maskell & Malmberg, 1999) such as the creative industries, which employ about 50% of employees in Greater London (DCMS, 2001)and represent 75% of Spanish activities in Barcelona and Madrid (DCMS, 2001; Lazzaretti & Parrilli, 2012).

Developing, maintaining, and building up tacit knowledge in a way that heterogeneity prevails is therefore key to increasing innovation and creativity in a RIS. In this context, we consider openness, in the form of social, cultural, and entrepreneurial openness of businesses integrating the RIS, as an essential variable for increasing the stock of tacit knowledge. The stock of tacit knowledge is the sum of cumulative distances of all tacit knowledge bases in the RIS. Thus, we relate openness to the cause (tacit knowledge increase) resulting in an employment increase in creative industries (Florida, 2007).

This position enables us to understand the underlying theoretical reason for this relationship and helps identify other possible variables (e.g., variety of professions, diversity of economy, tolerance, pluralism, internationality, mobility of the workforce, social capital) that may increase or activate the cumulative distance of all tacit knowledge bases in the RIS. For instance, a flexible labor law increases the mobility of the workforce, moving tacit knowledge from one company to another and introducing new tacit knowledge to the recipient company. Tolerance is another example: a tolerant society makes effective use of tacit knowledge that enters the RIS from other cultures.

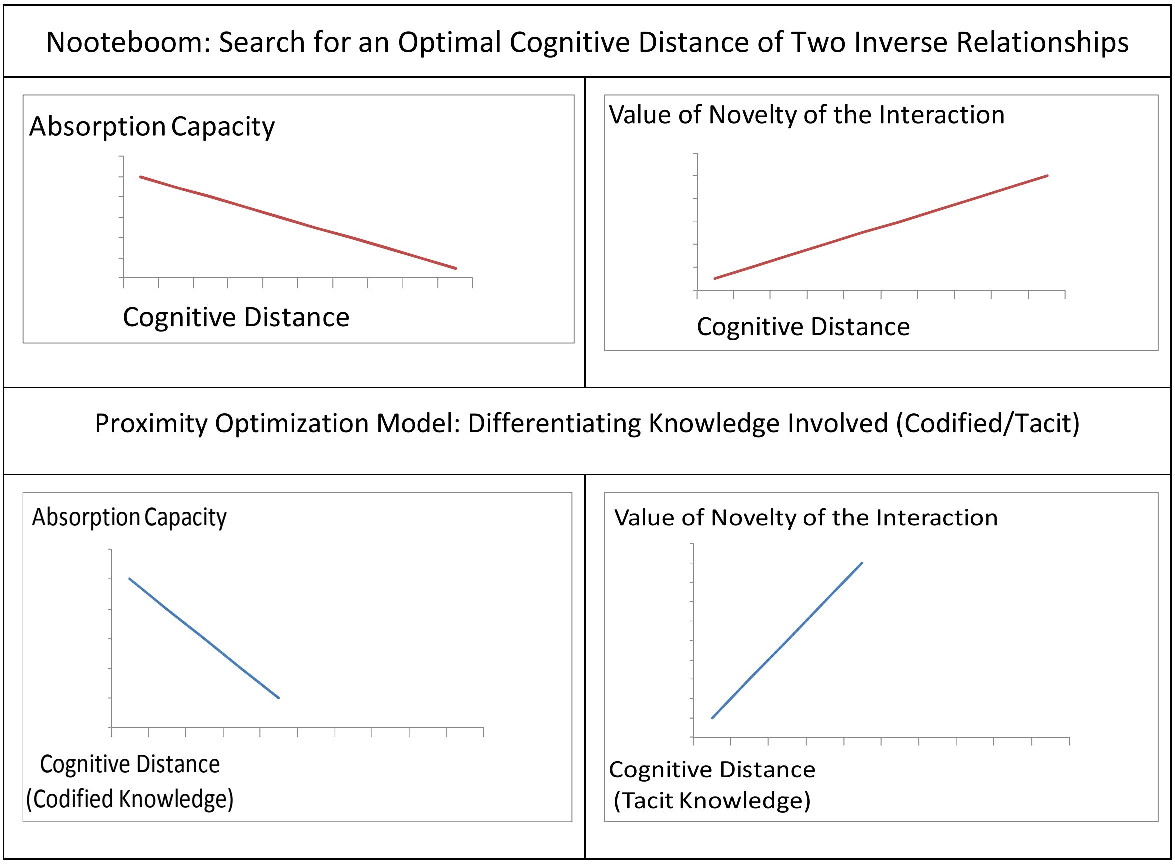
3.4. The Role of Openness in the Knowledge Creation Process

Our theoretical model is based on Boschma's proximity paradox and our proximity optimization model based on the distinction of codified and tacit knowledge (Broekel & Boschma, 2012; Unzalu, 2012). Boschma, based on Nooteboom (2007), investigated the effectiveness of collaboration between firms in terms of innovation outcomes. His research confirmed that cognitive proximity of two knowledge pools of cooperating firms ensures high absorptive capacity—the ability to identify, assimilate, and exploit knowledge (Cohen & Levinthal, 1990). If knowledge pools of the firms are too similar, however, the likelihood of an innovative recombination is lower than when two divergent knowledge bases are merged. This apparent tradeoff led to the formulation of the proximity paradox [(Broekel & Boschma, 2012): 7]

"While proximity may be a crucial driver for agents to connect and exchange knowledge, too much proximity between these agents on any of the dimensions [social, institutional, cognitive] might harm their innovative performance."

Figure 3.1 outlines the relationship. Reducing cognitive distance between two knowledge bases increases the absorption capacity of the agents involved, but the value and richness of a potential contribution of heterogeneous sources of knowledge of the interaction are also reduced. The approach to this inverse relationship stresses the importance of finding the optimal value.

Figure 3.1: Absorption Capacity and Cognitive Distance



Source: own elaboration.

Our model builds on the proximity paradox, based on the differentiation of codified and tacit knowledge. We argue the steepness of the relationship graphs depend on the knowledge type involved, allowing a more differentiated approach when finding the overall optimal value of cognitive distance between knowledge pools. Nooteboom's, Boschma's and Broekel's approach is to find a balance between the increase of absorptive capacity with the conditionality of allowing heterogeneous knowledge pools to merge; our approach is to identify codified knowledge stock investment as an instrument for increasing absorptive capacity, and tacit knowledge pools as instruments for increasing heterogeneity.

As we saw in the example of Atlantic tuna cultivation in fish farms, knowledge was exchanged in a joint project between the University of Kinki and the IEO to create a new, innovative product. This knowledge can be broken into its codified and tacit parts, Both organizations contributed formal codified knowledge to the project in the form of facts and laws, such as procedures for collecting eggs, data on lighting and feeding times, and structures of the fish tanks. Moreover, the inherent tacit knowledge of the experts and organizations, such as past experiences of failures or how a particular problem has been solved, was exchanged. Our example shows tacit knowledge can be exchanged only through joint work activities (i.e., the professor working during critical breeding times with the scientists of the IEO on site), and that it is very difficult to transmit such knowledge over long distances. Therefore, if dissimilar tacit knowledge bases are to be exchanged to produce significant innovation outcomes, they must be co-located. In contrast, codified knowledge stocks increase the absorptive capacity of the collaborating organizations, thus enabling distant collaboration.

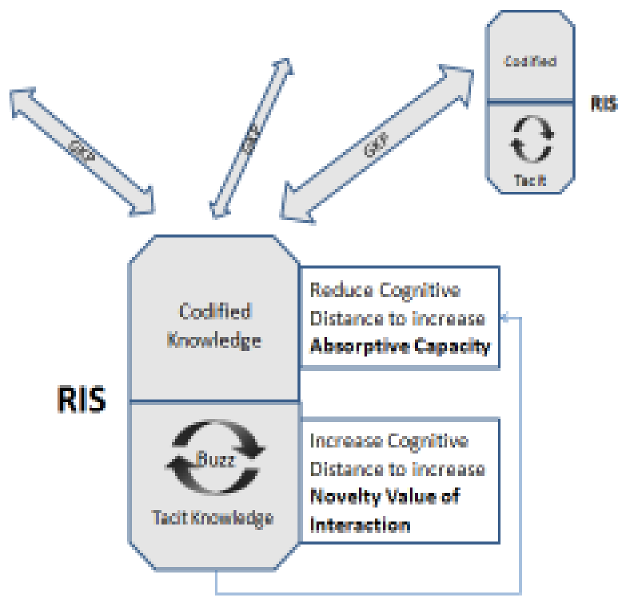
Before a joint project is started, it would be reasonable for firms to determine the organizational model of the collaborative project by identifying the knowledge types that are to be exchanged. In the context of a RIS, investment to increase stock of codified knowledge increases the absorptive capacity of the RIS, thus enabling distant, international collaboration through global knowledge pipelines (Bathelt, et al., 2004).

Dissimilar tacit knowledge bases available inside the RIS increase the value of interaction. Openness, with a constant flow of companies, people, and capital, increases the cumulative cognitive distance between the tacit knowledge pool and increases innovation in the region. It avoids lock-in caused by an excess of codified knowledge in relation to its tacit knowledge pool and provides a knowledge-based competitive advantage by increasing stickiness. The ever-increasing stock of codified knowledge and the role of social capital available in the RIS tend to decrease distance between tacit knowledge pools over time. Social capital refers to supportive social structures that facilitate coordinated action and collective learning. It connects various actors (and their tacit knowledge pools) available in the RIS through formation of discussion roundtables, interest groups, and common projects (Staber, 2007). Although this networking activity is a necessary means of exploiting the knowledge available in the RIS, it also constantly diminishes the cognitive distance of tacit knowledge between the actors if no further tacit knowledge pools enter the RIS.

The capacity to learn from tacit knowledge pools depends on the social relations surrounding production (Gertler, 2003); based on the implicit connection between social capital and tacit knowledge (Parrilli, 2012). High social capital increases the ability to learn and implies the cumulative cognitive distance of tacit knowledge pools is reduced.

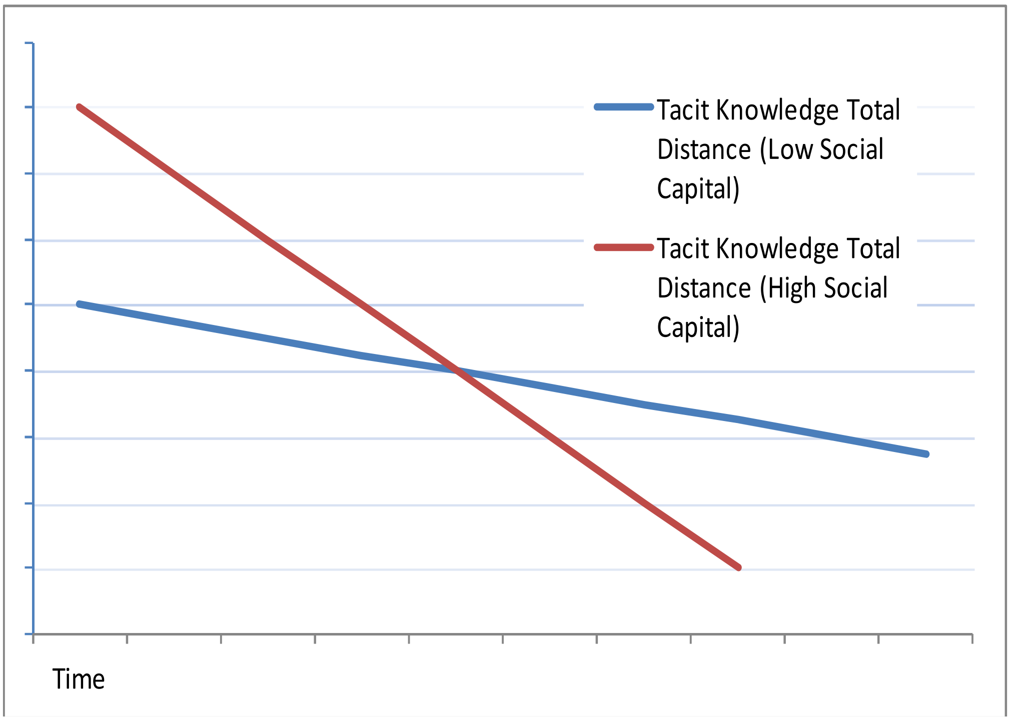
Therefore, openness can be seen as a counterbalance of shrinking cumulative tacit knowledge distance caused by the effect of social capital available in the RIS. The greater the social capital, the faster cognitive distance (tacit and codified) between actors is diminished. Codified knowledge can be complemented with knowledge outside the region through global knowledge pipelines, but tacit knowledge must be complemented by new pools - such as new groups of society (women, young, migrants, foreign firms) - entering the RIS. Figures 3.2 and 3.3 illustrate these relationships.

Figure 3.2: Collaboration in an RIS



Source: own elaboration.

Figure 3.3: Decreasing Tacit Knowledge Distance with Social Capital under the Constraint of No Further Tacit Knowledge Entering the RIS

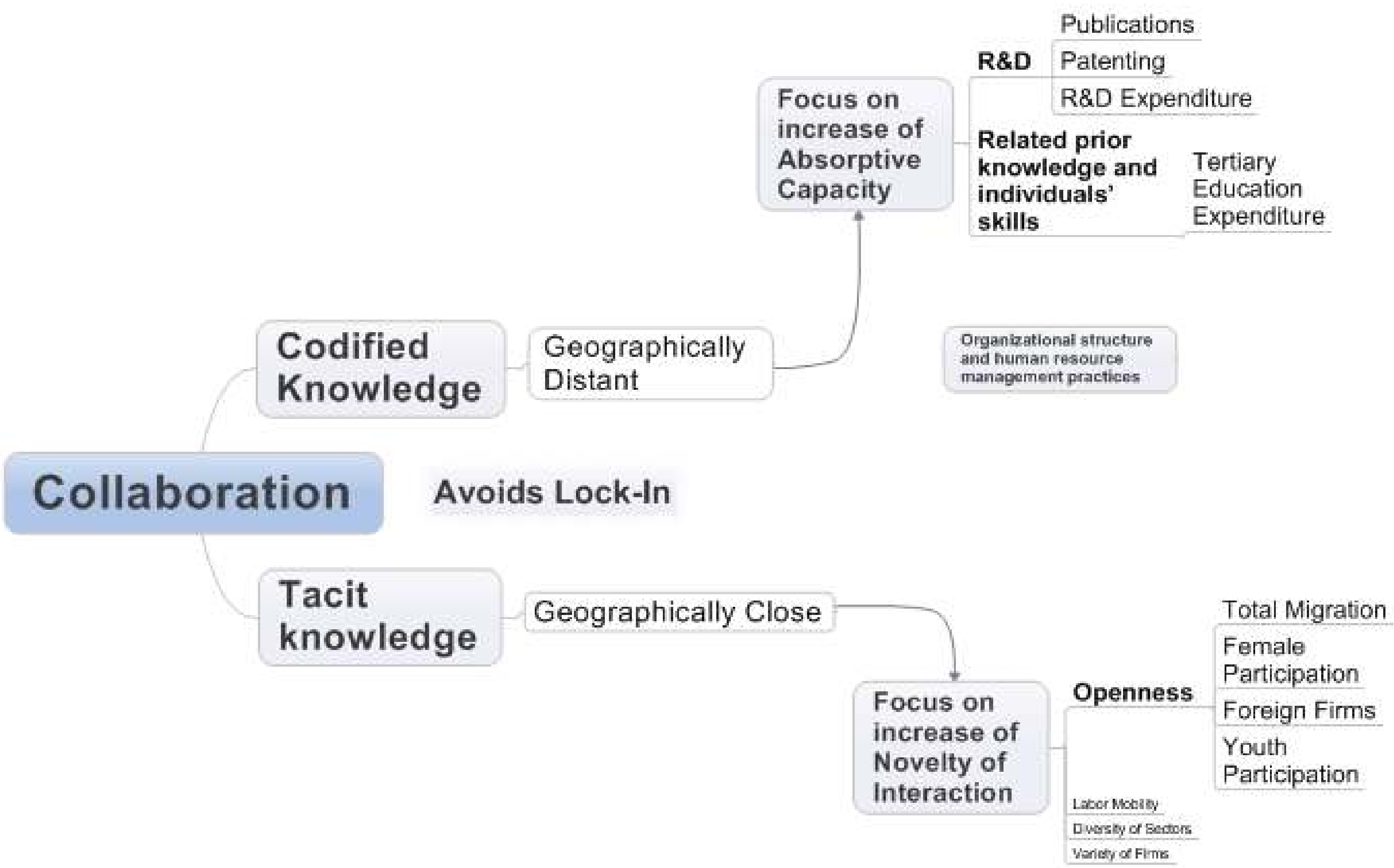


Source: own elaboration.

Simultaneous investment in research and development (R&D) and knowledge in individuals and skills helps increase the codified knowledge pool and reduce the cognitive distance from firms and organizations established in other RISs. Well-developed internal capabilities and resources in the RIS, in the form of infrastructure, education and training, and universities, also enhance the absorptive capacity of the firms and organizations in the RIS. We analyze R&D factors and prior codified knowledge and individual skills available in the RIS as proxies for the level of codified knowledge stock within European RISs. Openness variables, in the form of social, cultural, and business openness, are proxies for the tacit knowledge pools entering the RIS. This is based on the argument that migrations carry new tacit knowledge pools into the RIS and increase cognitive distance among local actors. People entering a RIS carry tacit knowledge from other regions; such knowledge increases heterogeneity and resourcefulness, such as business experiences from other regions and countries, and different attitudes and ways of working.

In addition, an inclusive society ensures organizations and firms are able to take advantage of the knowledge of different social groups, such as youth, men, or women, without discrimination. Foreign firms bring tacit knowledge into the RIS by transferring the work methods and collective insights, norms, and values of their home countries to the RIS. We propose a dynamic model by arguing that build-up of a stock of codified knowledge must be accompanied by an increase of heterogeneity in tacit knowledge pools. Tacit and codified knowledge interact along a continuum and converts it into new knowledge (Nonaka & Von Krogh, 2009). Different tacit knowledge bases convert the same codified knowledge into different types of knowledge held by individuals and groups, which can interact with each other and create something new based on the different knowledge held. In addition, new tacit knowledge bases are needed to prevent lock-in from too much codification of knowledge in relation to tacit knowledge (Cowan et al, 2000).

Figure 3.4: Collaboration and Knowledge Types



02/10/2013, own elaboration

To catch up, RISs may copy and adapt technologies developed elsewhere, manufacture at lower costs, or activate tacit knowledge pools by investing in social capital. Investing in codified knowledge increases absorptive capacity by reducing cognitive distance to other codified knowledge bases. But novelty of interaction is also reduced (Broekel & Boschma, 2012), making it necessary to find new knowledge bases. With increasing stock in codified knowledge and available social capital, local and heterogeneous tacit knowledge pools become more and more important for avoiding over-embeddedness or lock-in caused by an excess codified knowledge in relation to its tacit counterpart.

Moreover, tacit knowledge increases stickiness of knowledge and enables a competitive, knowledge-based advantage. The two knowledge types are complementary and can be used as predictors to estimate employment in the creative industries. In the next chapter, we present our econometric model and the results obtained.

3.5. Econometric Model

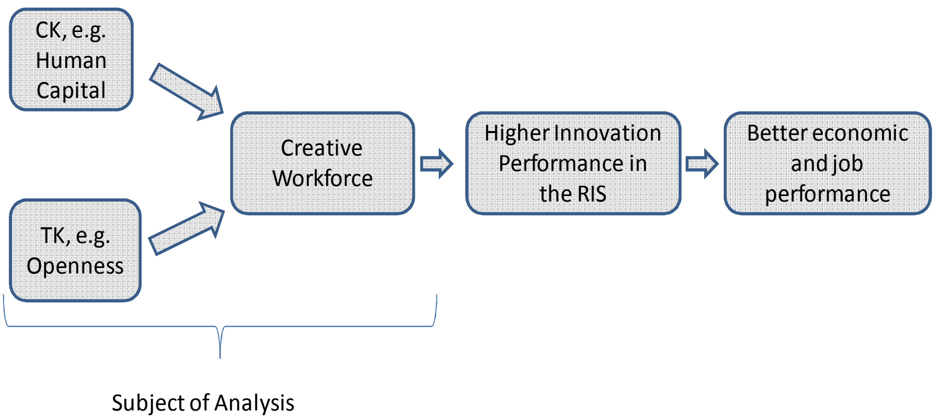
In line with the relevant literature, our proposed model identifies the presence of a creative workforce as a moderator towards higher innovation performance. Higher innovation performance in a RIS usually leads to better economic performance and job growth in the region. We investigate the role of the regional codified knowledge stock and the regional tacit knowledge stock, in terms of the cumulative cognitive distance to all knowledge bases (also variety), as critical input factors for the emergence of a creative workforce.

Investment in codified knowledge stock, such as tertiary education expenditure and R&D, increases absorptive capacity by reducing cognitive distance to other codified knowledge bases. Openness increases the ability of the RIS to receive diverse tacit knowledge pools embodied in individuals and organizations from other RISs. The sum of the cognitive distances between the local tacit knowledge pools resulting from the variety of actors from different backgrounds (e.g., various communities in the region) is the total cognitive distance between the tacit knowledge pools. The greater the variety of actors, the larger the cumulative cognitive distance in tacit knowledge available in the RIS, the greater the richness of regional interactions enabled by social capital, and the higher the chances for a creative outcome. Figure 5 displays the subject of analysis.

Four codified knowledge variables provide information on the codified knowledge stock available in a region; R&D-category variables include number of publications per million (hereafter *Publications*), number of patents per million (*Patenting*), and R&D expenditure as percentage of GDP (*R&D Expenditure*). The variable of percentage of labor force with tertiary education (*Tertiary Education*) provides information about prior knowledge and individual skills.

Publications is the process of putting knowledge on paper in codified form. The most typical example is the process of publishing in journals, which, identical to registering a patent (*Patenting*), provides information on the stock of codified knowledge available in the RIS (Haruyama, 2009). Available knowledge in the RIS is articulated in codified form (Cowan et al, 2000).

Figure 3.5: Codified knowledge, tacit knowledge, and creative workforce



06/09/2013, own elaboration

Intellectual human capital consists of research activities in the region (Haruyama, 2009). Human capital accumulates through schooling, on-the-job-training, and learning-by-doing. However, intellectual human capital is the most codified form of human capital. Scientific knowledge is codified (Cohen et al, 2000); *Tertiary Education* is the study of science completed by means of R&D. Indicators such as *Labor with Tertiary Education* measure the accumulation of codified knowledge inside the RIS.

With regard to tacit knowledge stock variables, our study focuses exclusively on openness variables and takes into account four indicators: Average total net migration (*Total Migration*), equal gender participation in the labor market (*Female Participation*), youth participation in the labor market (*Youth Participation*), and number of foreign firms in the RIS (*Foreign Firms*).

Our selection of tacit knowledge variables for the factor analysis is based on the tacit knowledge and openness and diversity literature. Tacit knowledge is embodied in individuals. Codified knowledge is written down and can be shared among individuals across large distances, whereas sharing of tacit knowledge involves people jointly creating a social environment or society. A common history, shared experiences, and a social and organizational frame enable tacit knowledge to be communicated and shared among the members of the community (Ancori, 2000). Individuals and groups of migrants can bring new tacit knowledge into the RIS, increasing the diversity of available tacit knowledge bases as measured by *Total Migration*. Through 'enfolded mobilities'[10] (Williams, 2009), tacit knowledge can be part of the skills set but also from knowledge that derives from socialization and acculturation in a different region as well as from using a different language, having a different culture, or from different working groups (A. M. Williams, 2007b).

These knowledge pools merge to create something new. For instance, social capital in the early development of the American film industry evolved through migration, with incoming players imitating ideas from various locations and creating new innovative variations (Staber, 2007). Diversity ensures an increase in total cognitive distance

[10] Enfolded mobilities is used by Williams (Williams, 2009) Enfolded mobilities are based on networks which produce enduring connections across space and through time between people and things. It can be differentiated contingent mobilities from collective mobilities. The former are consequential mobility when skilled migration generates demand for less skilled migrants in the service industries and the latetr are e.g. dependents moving with lead migrants). Five types of enfolded mobility are identified.

between tacit knowledge bases, which in turn raises numbers of interactions and triggers mechanisms for creating new knowledge (Bathelt, et al., 2004).

Therefore, the higher the rate of immigration, the more diversified tacit knowledge bases of the RIS become (Ancori, 2000; Hunt, 2009; Maskell, 1999; Yeung, 2011) and the higher the potential to implement tacit knowledge through cooperation (Ancori, 2000; Lundvall, et al., 2002). Migrants offer complementary capacities in management and entrepreneurial activity, resulting in better exploitation of R&D investment. In Silicon Valley, 14% of all firms are foreign-owned; 24% are led by Chinese and Indian immigrants who have set up operations in their native countries to access low cost labor and its domestic market (Saxenian, 2002c).

Female Participation in the labor market increases diversity of tacit knowledge bases in firms through an equal mix of gender. Similarly, *Youth Participation* in the labor market ensures a greater variety of tacit knowledge bases in the organizations by integrating all age groups. *Female Participation* and *Youth Participation* are thus indicators for openness of RIS organizations to participation of all groups of society.

The selection of variables Female Participation and Youth Participation is based on Lorenz et al. (2007), Hildrum (2009), and Perraton and Tarrant (2007), which have emphasized that the higher the number of apprenticeships accessed by the younger population, the more diversified tacit knowledge bases in the RIS become. As a logical consequence, this is also the case for women participating in equal terms in the labor market. *Youth Participation* is the difference of youth unemployment compared to overall unemployment rate in the region. Hence, *Youth Participation* takes into account differences in economic and job performances in the RIS, since regions of higher economic prosperity and better job performance also have lower unemployment rates.

The highest values (which signal low participation) are exchanged for lowest values in the data set (i.e., the highest value is exchanged for the lowest, the second highest with the second lowest and so forth). By means of this exchange, we are able to relate the lowest difference between these two values to the highest participation of youth in the labor market. Similarly, *Female Participation* is the difference of female participation in the labor market compared to overall participation. Subsequently, the highest value (indicating low participation of both gender) is exchanged with the lowest, the second highest with the second lowest and so forth. Therefore, the lower the value, the more even the distribution of men and women in the labor market.

Foreign Direct Investment (FDI) may enter the RIS or leave as a result of companies investing outside the RIS. Inward FDI enters the RIS and brings foreign tacit knowledge in, ensured by the ownership relationship outside the RIS. Ownership structure leads to tacit knowledge flowing into the RIS by means of worker mobility and exchange with the company´s headquarters (Cohen & Levinthal, 1990; Mendi, 2007; Perraton & Tarrant, 2007).

Nathan and Lee (2011) provide evidence that London firms with diverse ownership structure, teams, and management have been more successful in developing innovative products and processes. They further describe the links between cultural diversity and innovativeness at individual, firm, and city levels. Our final indicator, *Foreign Firms* in the region, is thus an indicator for external tacit knowledge entering the RIS. The selected codified and tacit knowledge variables are shown in Table 3.1.

Table 3.1: Codified and Tacit knowledge Variables

Independent Variable	Predictor	Source[11]
Codified Knowledge	Publications per million inhabitants, years analyzed 2000–2005: ***Publications***	ERAWATCH
	PCT patent applications per million inhabitants (fractional count; by inventor and priority year) – level, years analyzed, 2000-2007: ***Patenting***	OECD
	R&D Expenditure over GDP, years analyzed, 2000–2007: ***R&D Expenditure***	Eurostat
	Tertiary education (as % of labor force), years analyzed, 2000–2007: ***Labor with Tertiary Education***	(OECD)
Tacit Knowledge in form of Openness	Average total migration (population variation not explained by deaths and births) in % of total population, years analyzed, 2000–2007: ***Total Migration***	Eurostat Eurostat Eurostat
	Difference of Female participation rate in % to overall participation rate, years analyzed, 2000-2007: ***Female Participation***	Eurostat (OECD)
	Difference of youth unemployment rate in % to overall unemployment rate in %, years analyzed, 2000–2007: ***Youth Participation***	(OECD)

[11] Data provided by ORKESTRA, the Basque Institute of Competitiveness, and ESPON.

	Foreign Firms (Isla Bocconi) per million inhabitants, 2007: ***Foreign Firms***	(OECD)
Dependent Variable	**Response**	**Source**
Creative Workforce	Average creative workforce contingents per 1,000 head of active population, Active population is average population (2008): ***Creative Workforce***	Eurostat Labor Force Survey
Control Variable		**Source**
Population	Population on 1 January by age and sex - NUTS 2 region, years analyzed 2007: ***Population***	Eurostat

The response variable C*reative Workforce* has been facilitated by ESPON and is collected through the Eurostat Labor Force Survey. There are datasets for 2001–2004 and 2005-2008. To account for possible time lags, our analysis focuses on the latest available year (2008). *Creative Workforce* is defined and measured using the International Standard Classification of Occupations (ISCO) in selected ISCO-88 classes (4 digits).[12] In Europe, from 2005–2008, there were 19.2 million people representing 7.2% of the workforce classified in ISCO-88 professions. We also include the control variable of *Population* in our calculations. The control variable must remain constant throughout the experiment because it affects the other independent variables being tested and hence the outcome of the regression analysis. The control variable allows us to compare the results. All data is drawn from four sources: Eurostat, the Eurostat Labor Force Survey, the 2001 Eurostat Census at a regional level, and the OECD (2015).

[12] List of ISCO-88 4D codes: 2131 Computer systems designers and analysts, 2132 Computer programmers, 2139 Computing professionals not elsewhere classified, 2141 Architects, town and traffic planners, 2310 College, university and higher education, teaching professionals, 2320 Secondary education teaching professionals, 2431 Archivists and curators, 2432 Librarians and related information Professionals, 2442 Sociologists, anthropologists and related professionals, 2443 Philosophers, historians and political scientists, 2444 Philologists, translators, 2451 Authors, journalists and other writers, 2452 Sculptors, painters and related artists, 2453 Composers, musicians and singers, 2454 Choreographers and dancers, 2455 Film, stage and related actors and directors, 3131 Photographers and image and sound equipment operators, 3429 Business service agents and trade brokers not elsewhere classified, 3460 Social work associate professionals, 3471 Decorators and commercial designers, 3472 Radio, television and other announcers, 3473 Street, night club and related musicians, singers and dancers, 3474 Clowns, magicians, acrobats and related associate professionals, 3475 Athletes, sportspersons and related associate professionals, 3480 Religious associate professionals, 5113 Travel guides, 5210 Fashion and other models, 7311 Precision-instrument makers and repairers, 7312 Musical instrument makers and tuners, 7313 Jewelry and precious-metal workers, 7321 Abrasive wheel formers, potters and related, workers, 7322 Glass makers, cutters, grinders and finishers, 7323 Glass engravers and etchers, 7324 Glass, ceramics and related decorative painters, 7331 Handicraft workers in wood and related, materials, 7332 Handicraft workers in textile, leather and related materials, 7341 Compositors, typesetters and related workers, 7342 Stereotypes and electrotypers, 7343 Printing engravers and etchers, 7344 Photographic and related workers, 7345 Bookbinders and related workers, 7346 Silk-screen, block and textile printers.

3.6. Statistical Analysis

Only those European regions for which creative workforce data were available have been included in our study. For instance, no creativity workforce data were available for the German, UK and two Belgian regions. Data were available for a total of 176 NUTS-2 regions.[13] Predictor variables between the years 2000 and 2008 have been analyzed.[14] These predictor variables were analyzed with Creative Workforce variables in the same time period, i.e. from 2000 to 2008. Our analysis has taken the original values without normalizing for outliers, which could make the regression results less accurate (Montgomery, Peck, & Vining, 2012). However, outliers are rare in these types of variables.

We begin by analyzing the data through principal component analysis (PCA). Our hypothesis is based on the theory that input variables will group along two principal components, the codified knowledge component and the tacit knowledge component. This is a useful technique for variables that are closely related. Principal components regression works by first transforming the predictor variables using principal component analysis. Thereafter, the calculated initial loadings of each component are used to build the regression equation with creative workforce as output variable and population as the control variable.

The first step is to scale the original values, making their values comparable. Starting with 2000–2008 panel data of predictors only, values we analyze the scaled data matrix through a Principal Component Analysis. Data has been estimated for those years were no data was available. Next, we analyze 2008 data and identify possible lags by combining 2006 or 2007 input variables with 2008 output variables. We further analyze all single years from 2000–2008 to draw statistical conclusions.

[13] With exception of BE1: Brussels, which is a NUTS-1 region.
[14] With a few exceptions due to non-availability of data: Publications (2000–2005), International and national migration (2000–2007), Foreigners (only 2001), and Foreign Firms (only 2007).

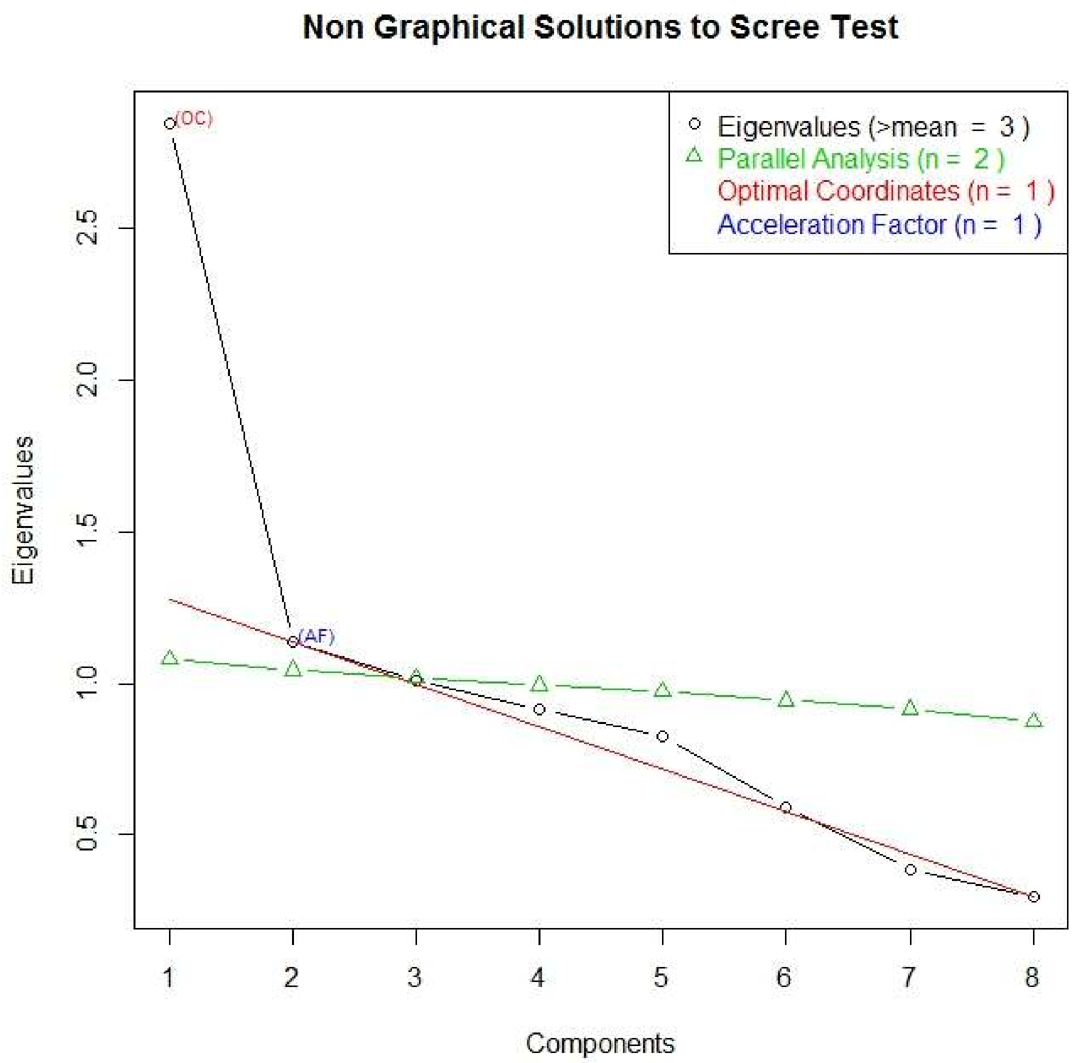
3.6.1. Principal Component Analysis

A PCA is a statistical procedure that reduces the complexity of the data set (Jolliffe, 2002). It fits an n-dimensional ellipsoid to the data, where each axis of the ellipsoid represents a principal component. PCA rotates the set of points around their mean to align with the principal components; it moves as much of the variance as possible into the first dimensions and drops those with little variance, with minimum loss of information. First, PCA selects the ellipsoid with the highest variance - the first principal component. Second, it identifies the data with the second highest variance under the constraint that it is uncorrelated with the first component.

The higher the variance, the more explanatory are the factors aligning to the component. The projections (shadows) in the form of arrows in Figure 4.7 show the direction of individual indicators and their importance. The longer they are, the higher the variance and the greater its importance. Such dimensionality reduction is a very useful step for visualizing the two knowledge components (i.e., tacit and codified knowledge) in the creativity process. European regions with high values of the workforce in creative industries should show balanced proportions of a codified knowledge and a tacit knowledge component.

Starting with 2000–2008 panel data, we first calculate the principal components of the scaled values. The graph in Figure 3.6 shows the principal components of the eight input variables:

Figure 3.6: Principal Components of 2000-2008 Panel Data



When deciding the number of components to retain, we must consider the amount of total sample variance explained, the relative sizes of the eigenvalues, and the subject-matter interpretations of the components (Johnson & Wichern, 2007). Most rely on the analysis of the eigenvalues of the correlation matrix and propose the scree test, a graphical strategy to determine the number of components to retain (Raîche, Riopel, & Blais, 2006).

By applying a visual aid, it is possible to determine the appropriate number, which is the elbow or bend when organizing the eigenvalues (as in Figure 4.6 in black colour) from highest to lowest. We can see a first bend at the second principal component, with the remaining components relatively small. This bend is also calculated by the Acceleration Factor (AF in Figure 4.6), which puts emphasis on the coordinate where the slope of the curve change abruptly (Raîche, Riopel, & Blais, 2006).

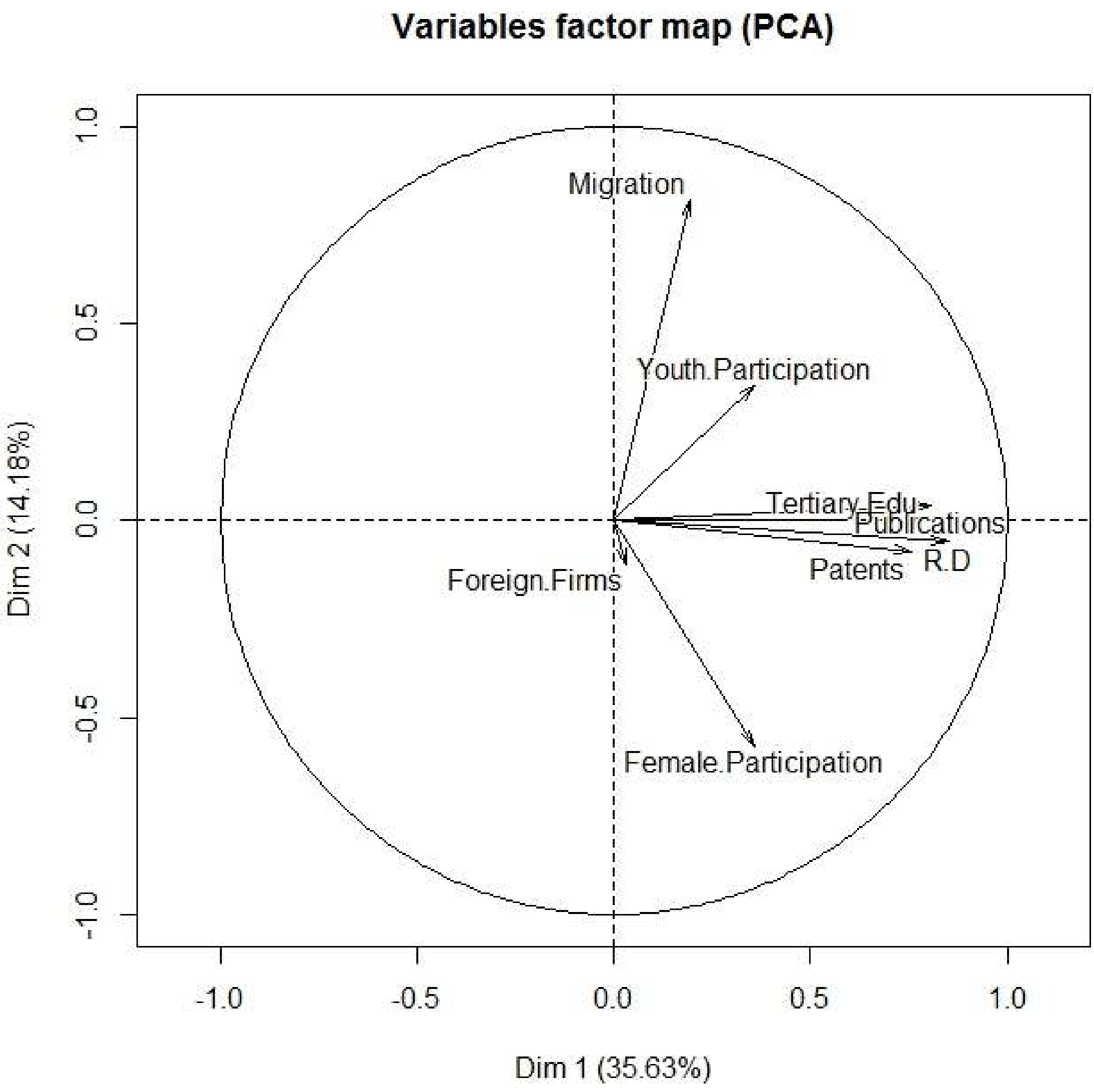
Other solutions to determine the number of components to retain are the Kaiser-Guttman rule and the Parallel Analysis. The factor with the largest eigenvalue has the most variance down to factors with small eigenvalues. According to the Kaier-Guttman rule, from an analyst perspective it makes no sense to analyze eigenvalues below 1.00, which occurs around component three onwards (Raîche, et al., 2006). However, the Kaiser-Guttman rule does not provide us with an answer wheather to retain or exclude component three since it is around 1,00. Moreover, this rule can be misleading for finite observations as in this case (Raîche, et al., 2006).

The Parallel Analysis retains only eigenvalues of the principal components that are superior or equal to the average of the eigenvalues (see green line in Figure 4.6) (Raîche, et al., 2006). Here, we can see that the green line is slightly above the eigenvalue of component three. Therefore, two principal components effectively summarize the total sample variance.

The hypothesis is that two factors, codified and tacit knowledge explain the creativity in the RIS. Therefore, the selection of two factors based on Scree test, the Kaiser-Guttman rule and the Parallel analysis have confirmed that two factors are to be retained, which may help in the interpretation of the results.

Figure 3.7 shows the input variables organized around the two principal components.

Figure 3.7: Variables Factor Map of 2000-2008 Panel Data Input Variables



The Variables Factor Map above demonstrates the importance of the two components, showing Component 1 explains approximately 36% of the variance and Component 2, 14%. Therefore, the two principal components combined explain 50% of the variance. Moreover, the length of the arrows indicates their importance and their alignment with the two principal components. We can see that according to our hypothesis, codified knowledge variables group along Component 1, whereas *Migration* and *Youth Participation*, as well as *Female Participation* group on the second component, but in opposite directions.

Nevertheless, we also need to stress that principal components three to eight, i.e. the rest of the components, explain the remaining 50% of the variance. Therefore, there is a lot of information left out that explain tacit and codified knowledge in the RIS, in addition to the two principal components selected. For instance, the presence of foreign firms is neither relevant in factor one nor two. Nevertheless, the initial loading component 3 of Foreign Firms is with -0,97 extremely high, which is shown in table 4.2 below. Here, we show the initial loading components for each indicator through factor analysis. Factor analysis describes the covariance relationships among the two groups of variables, as we summarize in Table 4.2.

Table 3.2: Factor Analysis of 2000-2008 Panel Data

Indicator	ILC 1	ILC 2	ILC 3	ILC 4	ILC 5	ILC 6	ILC 7	ILC 8
Migration	0,12	0,76		-0,12	0,50	0,35		
Female Participation	0,21	-0,54	0,18	0,31	0,70	0,20		0,14
Youth Participation	0,21	0,32		0,87	-0,14	-0,25		
Foreign Firm		-0,11	-0,97	0,16		0,12		
Publications	0,48			-0,24		-0,42	-0,59	0,43
Patents	0,44				-0,44	0,50	0,33	-0,71
R&D Expenditure	0,50				-0,13	0,33	-0,32	-0,71
Tertiary Education	0,46			-0,20	0,17	-0,48	0,66	-0,21
Importance of Components								
Standard Deviation	1,69	1,07	1,00	0,96	0,91	0,77	0,62	0,54
Proportion of Variance	0,36	0,14	0,13	0,11	0,10	0,07	0,05	0,04
Cumulative Proportion	0,36	0,50	0,63	0,74	0,84	0,91	0,96	1,00
Eigenvalues	2,85	1,13	1,00	0,91	0,82	0,59	0,39	0,29

ILC: Initial Loading Component

Factor analysis confirms that all tacit knowledge indicators except *Foreign Firms*, which entirely aligns along Initial Loading Component 3, show significant values in Initial Loading Component 2. This means that *Foreign Firms* is not among the two most significant components. Component three explains 13 % of the variance attributable to Foreign Firms. Therefore, the presence of Foreign Firms in the RIS does not contribute to the first two loadings, but contributes negatively to Creative Workforce through initial loading three. Hence, tacit knowledge might be explained by more than one factor alone. For instance, initial loading component 4, which explains 11% of the variance, also show high values of *Youth Participation* (0.87).

In summary, the contribution of tacit knowledge in explaining *Creative Workforce* is far more complex than codified knowledge. It seems that tacit knowledge should be calculated by means of one factor. Codified knowledge indicators concentrates its contribution in principal component 1, and show only significant values from initial loading component 6, whose contribution of the component to Creative Workforce is insignificant. Tacit knowledge indicators and codified knowledge indicators contribute in different ways towards a *Creative Workforce*. Codified knowledge is summarized very well by one component alone while tacit knowledge has also values in other components, although several tests such as the Parallel test suggest retaining only one component.

Within the two principal components it is clear what dominates is mostly codified knowledge, since the other variables enter with less weight. Regarding tacit knowledge component 2, one the one hand, *Migration* and *Youth Participation* have opposite values to *Female Participation* in the labor market, but on the other hand, the high values of codified knowledge components, which group along Initial Component 1, show significant values in the same direction. Therefore, factor rotation (i.e., factor loadings obtained from initial loadings by an orthogonal transformation) should not provide better results; we confirm this by calculating the values through Varimax rotation.

The negative value of *Female Participation* means that this indicator is contributing in negatively to creative Industries.

The initial loading components provide higher values and are better suited for the analysis. Our Cronbach's alpha test on 1,584 observations - the total number of observations -, which tests the results for consistency, shows an alpha value of 0,7. Cronbach's alpha is a measure of the internal consistency of a scale. The higher the proportional variance between the regions, the higher the alpha value and the consistency of the scale. A value around 0.7 can be regarded as acceptable (N. Schmitt, 1996).

3.6.2. Panel Data Analysis

After calculating the initial components, we are able to perform panel data analysis using the components constructed above as regressors:

Formula 3.1: Ordinary Least Squares Regression Model:

$$Y_i = \beta_0 + \beta_1 \text{Codified Knowledge Component} + \beta_2 \text{ Tacit Knowledge Component}$$

where Y= Creative Workforce

Here, panel data include time series between 2000 to 2008 of the independent variables (predictor variables) and the dependent variable. We have chosen to analyze this data by means of factor analysis for various reasons. The interest in factor analysis is centered on the parameters that the factor model delivers (Johnson & Wichern, 2007). The principal component analysis performed in the previous chapter was based on a theoretical analysis that codified and tacit knowledge variables group along two basic lines that explain *Creative Workforce* and which are orthogonal to each other. This means that codified and tacit knowledge act in a complementary way. This was confirmed by the empirical analysis that two components are to be retained.

To complete this analysis, principal component analysis can be complemented by a principal component factor analysis, since the latter's essential purpose is '*to describe the covariance relationships among many variables in terms of a few underlying, but unobservable, random quantities called factors'* [(Johnson & Wichern, 2007): 481]. Hence, the idea is to check the possibility of summarizing the codified knowledge variables into factor 1, and tacit knowledge variables into factor 2 and run with these two factors a regression analysis to estimate *Creative Workforce*.

This analysis is suitable when it is suspected that variables can be grouped by their correlations. We could see in the previous chapter, that codified knowledge variables were highly correlated among themselves, but have relatively small correlations with tacit knowledge variables. Therefore, and based on our theory of the complementary role of codified and tacit knowledge, it is conceivable that each group of variables represent a single underlying construct, i.e. factor.

We could also see that this is the case for the tacit knowledge variables, although some variables, such as *Foreign Firms,* do not group with the rest of the tacit knowledge variables. Moreover, *Female Participation* contributes negatively in principal component two. Although it is likely that these two variables do not contribute in improving the accuracy of the model, we nonetheless follow the model that only two components have to be retained.

To group the variables into two factors allows a better interpretation of the results, since factor analysis provides a way of explaining the underlying unobservable traits (Johnson & Wichern, 2007), which is exactly what we intend to do. Moreover, by means of using both factors as predictors, we are able to calculate the accuracy of the model by means of regression analysis (see formula 4.1 above).

However, panel data has some drawbacks when it is analyzed through multi linear regression based on ordinary least squares (OLS). For instance, we have repeated observations per region since the panel data covers 8 years. Therefore, observations are not independent, although they do allow us to get better estimates (Greene, 2003). These fixed effects caused by cross-region dependency or correlations between countries can be sorted by means of a dummy variable for a small number of individuals, but not for that many regions in Europe as in this case.

Therefore, there are two techniques that can be used to analyze panel data: Fixed effects and Random effects. The, the Hausmann tests is applied to check which one of these methodologies should be applied.

The fixed effects model takes into account that each region has a fixed effect that shifts the regression line up or down. In contrast, the random effects model treats each independent variable as if they arise from random causes. The Hausman-test allows us to analyze the consistency of the methodology applied by comparing the fixed effects and the random effects model based on which model delivers higher efficiency (Greene, 2003). Below the formula of the fixed effects model:

Formula 3.2: Fixed Effects Model:

$$Y_{it} = \beta_1 Factor\ 1_{it} + \beta_1 Factor\ 2_{it} + \alpha_i + u_{it}$$

where
– αi (i=1….n) is the unknown intercept for each entity (n entity-specific intercepts).
– Yit is the dependent variable Creative Workforce where i = entity and t = time.
– β1 is the coefficient for that IV,
– uit is the error term

The fixed effects model analyses variable Creative Workforce over time within the region (Torres-Reyna, 2007). Each region has its own individual characteristic when influencing the dependent variable Creative Workforce and the fixed effect model controls for this unique effect, which is valid to the region alone. Therefore, it removes the effect of time-invariant characteristic and allows determining the net effect of the 2 Factors on the dependent variable. However, if the error terms are correlated, then the fixed affects model is not suitable and the relationship needs to be explained by the random effects model (Torres-Reyna, 2007). Running an OLS regression function provides us with the following results :

Table 3.3.: Results of the Ordinary Least Squares Analysis with Factor 1 and Factor 2 as independent variables and Creative Workforce as dependent variable:

Balanced Panel: N=176, t=9, N=1584	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**
(Intercept)	-0.0067	0,017	-0,390	0,6969
Factor 1	0.3923	0,0102	38,524	< 2e-16 ***
Factor 2	0,0565	0,0161	3,505	0,00632 **

Population (Control Variable)	0,0472	0,0173	2,734	0,00632 **
Residual Sum of Squares: 0,6811 on 1580 degrees of freedom				
R-Squared: 0,493				
Adj. R-Squared : 0.492				
F-statistic: 512.1 on 3 and 1580 DF, p-value: < 2.2e-16				

Significance Codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

The result of the OLS Analysis in Table 4.3 above indicates that both factors including the control variable are significant and explain the dependent variable Creative Workforce with an R-squared of 0,49. The figures 4.8 and 4.9 show the individual factors in relation to the dependent variable Creative Workforce. Subsequently, we analyze the panel data with the fixed effects model whose results are shown in table 4.4. below:

Table 3.4.: Results of the Fixed Effects Analysis with Factor 1 and Factor 2 as independent variables and Creative Workforce as dependent variable:

Balanced Panel: N=176, t=9, N=1584	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**
Factor 1	0.275563	0.032914	8.3721	< 2e-16 ***
Factor 2	-0.033841	0.017480 -	1.9360	0.05306 .
Population (Control Variable)	0.571678	0.263166	2.1723	0.03000 *
Total Sum of Squares: 227,25				
Residual Sum of Squares: 214,43				
R-Squared: 0,056				
Adj. R-Squared : 0,050				
F-statistic: 42.0065 on 2 and 1406 DF, p-value: < 2.22e-16				

Significance Codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

The result of the fixed effects analysis with significant p-values in factors 1 and the control variable, but not significant in factor 2. Therefore, this model tells us that only Factor 1 has a significant influence on dependent variable Creative Workforce. Moreover, the p-value in the F-statistic[15] indicates that the model is valid. The next table 4.5 shows us the results of the random effects model. Here, no fixed effects are assumed in the panel data:

Table 3.5.: Results of the Random Effects Analysis with Factor 1 and Factor 2 as independent variables and Creative Workforce as dependent variable:

Balanced Panel: N=176, t=9, N=1584	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**
Intercept	-0.0066676	0.0434284 -	0.1535	0.87800
Factor 1	0.3519626	0.0204025	17.2510	< 2e-16 ***
Factor 2	-0.0293181	0.0161497 -	1.8154	0.06965 .
Population	0.0571265	0.0431381	1.3243	0.18560
Effects	**Variance**	**Standard Deviation**		**Share**
Idiosyncratic	0,1525		0,3900	0,328
Individual	0,3118		0,5584	0,672
Theta	0,7732			
Total Sum of Squares: 289,9				
Residual Sum of Squares: 243				
R-Squared: 0,1628				
Adj. R-Squared : 0,1623				
F-statistic: 102.408 on 3 and 1580 DF, p-value: < 2.22e-16				

Significance Codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

In the random effects model, again only factors 1 is highly significant and has therefore a significant influence on the dependent variable. Neither Factor 2 nor the control

[15] The F-statistic is a test (F) to see whether all the coefficients in the model are different than zero.

variable are significant and have a significant influence on Creative Workforce. In addition, the model can be considered to be correct since the F-Statistic is highly significant. The Hausman-test confirms that the fixed effects model should be the preferred model to use compared to the random effects model.[16]

Therefore, the fixed effects model does not provide clear results as to use factor 2 as coefficient. Neither a Varimax rotation provides better results nor the inclusion of another factor three. Calculating the regression function by means of three factors instead of two only improves the R-squared by 2 decimals. Therefore, the regression analysis is performed with two factors only and an error variable as a dummy. This regression function will provide us with sufficient information on the validity of the concept in that factors are analyzed with respect to their impact, their significance, the overall accuracy of the model according to the region, and possible time lags.

[16] chisq = 19.3712, df = 3, p-value = 0.0002291. Alternative hypothesis: one model is inconsistent. Fixed effects should be used.

Figure 3.8: Ordinary Least Squares Regression with Factor 1 as independent variable and Creative Workforce as dependent variable

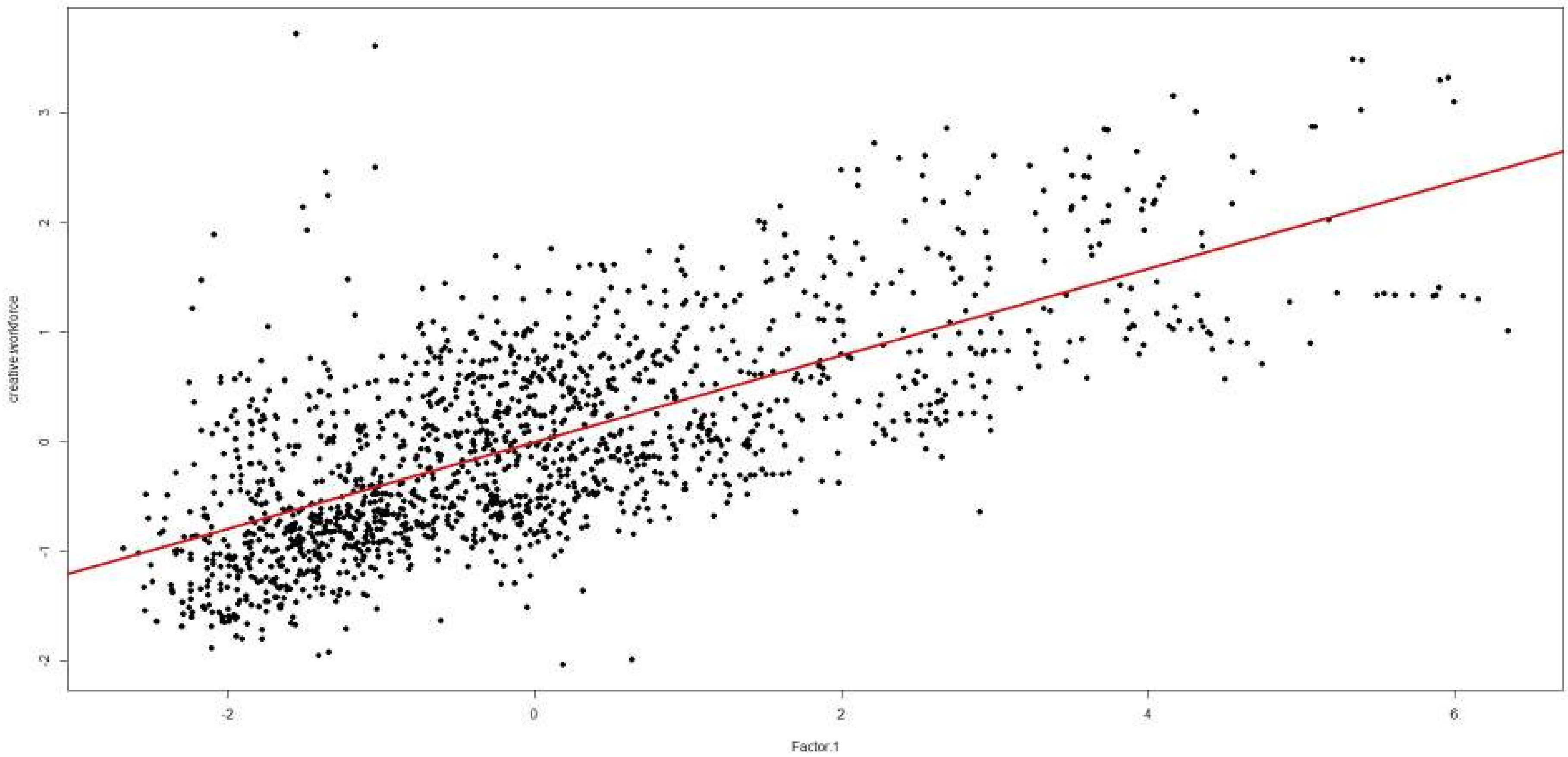


Figure 3.9: Ordinary Least Squares Regression with Factor 2 as independent variable and Creative Workforce as dependent variable

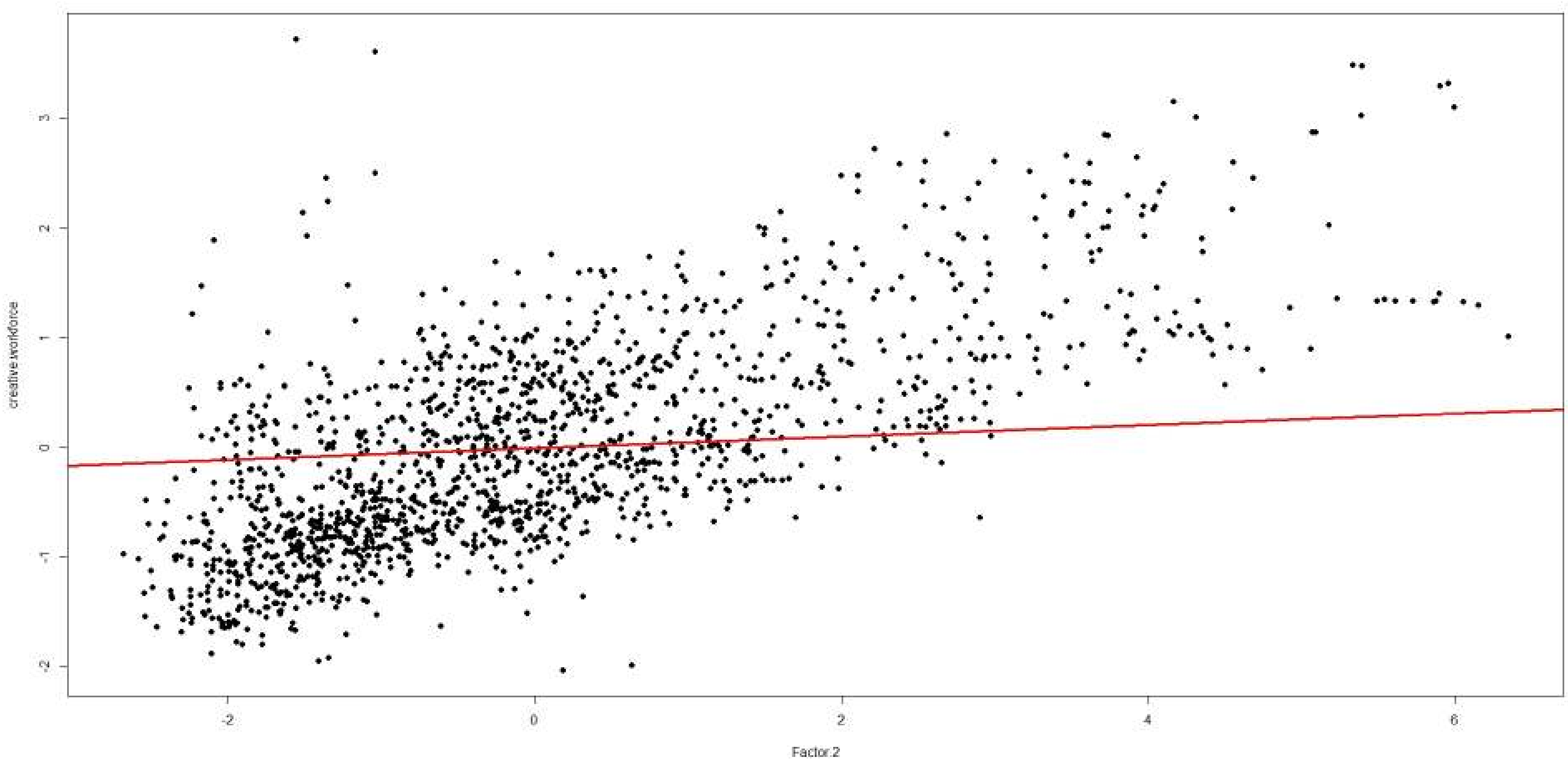


Figure 3.10: Predicted vs. Real Values of Creative Workforce in European Regions through the Principal Components Regression with Panel Data 2000–2008

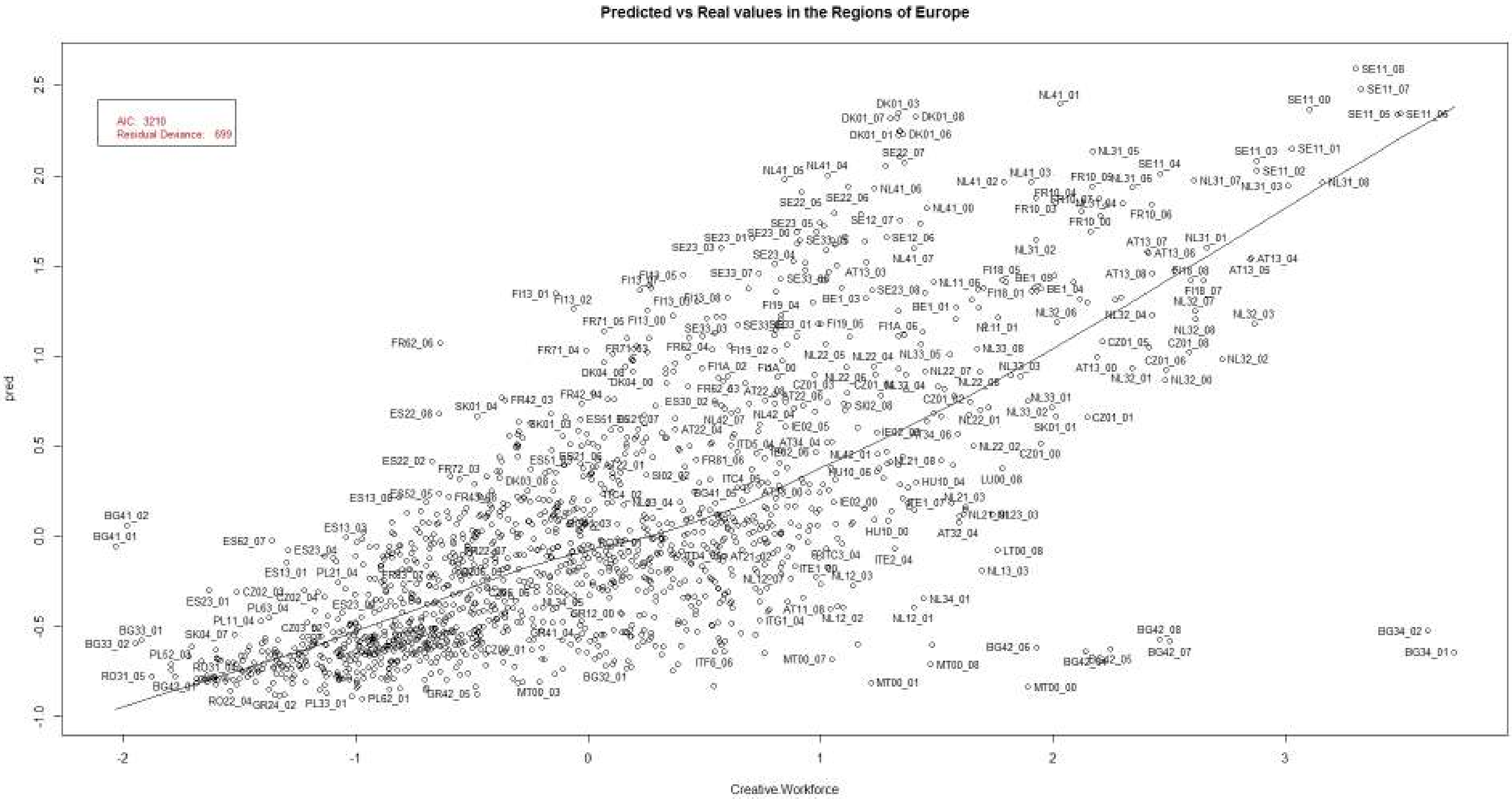


Table 3.6: Principal Component Regression Main Values, Panel Data and on a Yearly Basis with Creative Workforce as Dependent Variable

	Panel 2000-08	08-08	07-08	06-08
α	-0,006668	8,39E-14	1,037e-16	9,021e-17
Factor 1	**0.392317*** **	4,01E+02***	-4,029e-01***	**3,958e-01*** **
Factor2	**0.056532*** **	1,88E+02***	1,291e-01**	**3,451e-02**
Population	**0.047198*** **	6,66E+01	5,040e-02	5,710e-02
Creative Workforce	X	X	X	X
AIC	**3284,7**	377,37	382,79	**393,09**
R^2	0,49	0,53	0,51	0,48
F	512.1 on 3 and 1580 DF	63,42 on 3 and 172 DF	59,76 on 3 and 172 DF	53,1 on 3 and 172 DF
Alpha	0,66	0,67	0,71	0,68
Nr. Obs,	1,584	176	176	176

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Indicator	Panel 2000-2008		2008-2008		2007-2008		2006-2008	
	Loading 1	Loading 2	Loading 1	Loading 2	Loading 1	Loading 2	Loading 1	Loading 2
Migration	0,12	0,76	0,16	0,63	-0,12	0,72	0,13	0,76
Female Participation	0,21	-0,54	0,18	-0,68	-0,16	-0,65	0,16	-0,55
Youth Participation	0,21	0,32	0,24	-0,24	-0,25	-0,13	0,29	0,11
Foreign Firm		-0,11		0,24				0,16
Publications	0,48		0,48	0,14	-0,48	0,11	0,47	
Patents	0,45		0,45		-0,46	-0,10	0,44	-0,22
R&D Expenditure	0,50		0,50		-0,51		0,50	-0,11
Tertiary Edu.	0,46		0,45		-0,46	0,11	0,46	0,17
Standard Deviation	1,69	1,07	1,71	1,06	1,72	1,09	1,73	1,06
Proportion of Variance	0,36	0,14	0,37	0,14	0,37	0,15	0,37	0,14
Cumulative Proportion	0,36	0,50	0,37	0,51	0,37	0,52	0,37	0,51

Figure 3.8 shows the real versus the predicted values of European regions through Principal Component Regression with panel data of 2000–2008. Some European regions are on the line; others show higher-than-calculated creative workforce (or the reverse).

Table 3.6 shows the results of principal component regressions for the panel data 2000–2008 and the data for individual years (when input data and output data are from the same year). The possibility of time lags between input and output is taken into consideration but no evidence is found (negative values in 2007 input data and 2008 output data and not significant for 2006 input data and 2008 output data).

Our results confirm that only one component of the principal component regression equation is significant and positive. With panel data of 1,584 observations, the calculated R-square is 0.49. Nevertheless, the fixed effects model resulted in the conclusion that only the first factor is significant.

We see that loadings of codified knowledge indicators are significant and group along Loading 1, whereas loadings of tacit knowledge indicators are partly significant and group along Loading 2, except for *Foreign Firms,* which group negatively along a third component.[17] The *Foreign Firms* indicator is not significant, which might be explained with that our hypothesis that this indicator brings in tacit knowledge is not correct and that it rather brings in different capabilities or resources than tacit knowledge. *Female Participation* shows a negative value (–0.54), whereas *Youth Participation* (0.32) and *Migration* (0.76) show significant and positive values.

Therefore, all these indicators are relevant as a second principal component. Nevertheless, *Female Participation* seems to have a negative contribution to creative industries. Moreover, *Foreign Firms* also contributed negatively in the third component to *Creative Workforce.* The same conclusion can be drawn for the analysis of individual years such as 2008 (08–08). The fact that these two variables contribute negatively or not at all to the tacit knowledge factor 2 might be the reason for factor 2 not being significant in the fixed effects model.

By analyzing the loadings, we can confirm that codified knowledge indicators align in the same direction and are significant for the panel data as well as for all individual years. However, this is not the case for the tacit knowledge indicators. Clearly, the indicator *Migration* is positive and highly significant, aligning with Loading 2. For the panel data as

[17] see previous chapter

well as for all individual years, *Youth Participation* also aligns with Loading 2 in the case of the panel data and for some individual years. Two indicators, *Foreign Firms* in the region and *Female Participation* in the labor market, show negative values. This is probably the reason why the principal component regression function is less accurate than expected.

3.7. Conclusions

The findings on the first factor, i.e. codified knowledge, confirm previous studies by Florida and others (2006) that technology and talent leads to higher creativity in regions. Regarding the impact of the tacit knowledge factor, we cannot confirm that tacit knowledge has a positive impact on creative industries since it is not significant in the fixed effects model resulting in no clear results. The impact of the individual indicators that compose the tacit knowledge factor vary substantially. Migrations are by far the most important indicator, which led to its further analysis in chapter four. Whereas more analysis is needed with regards to Female Participation and Foreign Firms, that resulted in an inaccurate and not significant Factor 2.

We analyzed panel data from 2000–2008 (1,584 observations) through a principal component regression. Both loadings, representing the codified knowledge variable and the tacit knowledge variable, show positive and significant values individually. Nevertheless, the complementary role of codified knowledge for the presence of *Creative Workforce* cannot be confirmed. This could be the result since the principal component analysis also shows that not all openness indicators align along the same principal component: *Foreign Firms* does not align along the same component as *Migration*, *Youth Participation* and *Female Participation* in the labor market, but contributes negatively by means of a third component. *Youth Participation* and *Migration* are opposed to *Female Participation*, meaning that although all three indictors are relevant, *Female Participation* seem to contribute negatively to creative industries.

Overall, *Migration* is the most important indicator in the second principal component, (positive and significance for *Creative Workforce* in a region analyzed through a principal component regression). Therefore, although the indicators identified as codified knowledge indicators are grouped along Component 1, different results were obtained for the tacit knowledge components. Our analysis shows no evidence for the presence of lags between codified and tacit knowledge variables and *Creative Workforce*.

From our findings, we conclude that the complementary role of *Migrations* and *Youth Participation* and R&D investment in the form of *Publications*, *Patenting*, *R&D Expenditure*, and *Tertiary Education* needs further investigation. However, we cannot confirm the role of *Female Participation nor Foreign Firms*. More research in this area is required.

Our paper builds on the proximity paradox work of Nooteboom and Boschma (Broekel & Boschma, 2012; Nooteboom, 2007) by assessing an evolutionary theory of the proximity paradox and applying the critical role of the 'creative class' (Florida, 2002b) to Regional Innovation Systems (Cooke & De Propris, 2011). Our findings suggest case studies are needed to understand the role of a highly inclusive labor market in the creative class and to determine whether some regions prioritize an inclusive labor market as a substitute for migration. It may be helpful to investigate regions in other continents such as North America.

A principal shortcoming of our analysis is that we cannot confirm all tacit knowledge indicators align along the same principal component. Therefore, while both components are positive and significant for the regression analysis, prediction and accuracy is lower than expected. Future research should focus on building a better and more accurate tacit knowledge component. Nevertheless, our research has applied an innovative approach to the origins of a highly creative workforce in European regions. With the publication of new data sets, it will be possible to further analyze the relationship between tacit knowledge and the creative workforce, especially in the case of migration.

CHAPTER 4

OPENNESS AND INNOVATION IN REGIONAL ECONOMIES: THE ROLE OF MIGRANTS

4. Openness and innovation in regional economies: The role of migrants

4.1. Introduction

Historically scientific progress has been dominated by countries in Europe or North America and Japan, but scientific activity in the twenty-first century is characterized by increasing globalization. Research coming from Europe and North America is enriched by research elaborated in countries in Africa, South America, the Middle East, and throughout Asia. For example, China alone has increased its world share of research papers published in the Web of Science from 5.6% in 2003 to 14% in 2012 (Reuters, 2013). Nations with mature scientific enterprises also enjoy increased scientific production, but developing countries expand faster and thereby shift relative world shares in the publication market, such that they become more equally distributed geographically. Such shifts are evident in the number of nations involved in R&D activities, registered patents, and citations, which are indicators of the quality of the research activity. In turn, these trends provide opportunities to accelerate the speed of human knowledge creation through collaborations with a wider range of partners.

These elements mostly pertain to codified components of knowledge, that is, those aspects that can be written down in formulas, texts, and manuals and transferred over distances through various information and communication technology (ICT) systems. Another component of knowledge is equally crucial though, namely, tacit knowledge that cannot be written down in texts or manuals and that its possessor might not even be explicitly aware of (Michael Polanyi, 1966). Formally, tacit knowledge is “tied to the senses, skills in bodily movement, individual perceptions, physical experiences, rules of thumb, and intuition” (Von Krogh, Ichijo, & Nonaka, 2000).

Since tacit knowledge is not encoded, it may be transferred only by working together, in frequent, close contact (Perraton & Tarrant, 2007) and through intense, long-standing practice. Thus, it is less geographically mobile than codified knowledge. Increasing globalization in R&D activities and radical improvements in ICT have facilitated the accessibility of codified knowledge, yet both knowledge types need to grow together (Cowan et al, 2000). Excess codification can create cognitive lock-in, such that actors rely on obsolete technology regimes, or it may undermine regional competitiveness, because it is easy to copy and move to other regions. In contrast, tacit knowledge is more differentiated, granting companies and regions a difficult-to-copy competitive advantage (J. Kay, 1999). Thus benefits accrue from the complementary application of both knowledge types. Furthermore, tacit knowledge, unlike codified knowledge, is excludable; learning thus is as costly as acquiring codified knowledge (Nonaka & Takeuchi, 1994; Michael Polanyi, 1966).

Organizations also maintain tacit knowledge that might be codified, because over years of research, they simply have not been able to write down all their interactions and experiences in clear synthetic models or manuals. Scarce resources also would need to be applied to codify tacit knowledge, which would limit their application elsewhere, such as for engaging in research at the knowledge frontier. In turn, we anticipate that codified knowledge growth is constrained by the growth of tacit knowledge pools (Cowan et al, 2000). Tacit knowledge grows through building diverse stocks of knowledge, held by all individuals and agents in a region. The more diverse the social fabric, the more tacit knowledge is available. The resulting higher stock of tacit knowledge in a region makes it unique.

In this context, immigrants offer a valuable source of variety in tacit knowledge pools for a region. Often they have progressed through a different schooling system, adopt own learning schemes, and have had different life experiences, so they are likely to introduce alternative ways to solve problems. We note inward migrations and the ability to use foreign-based tacit knowledge productively, in either an exploitation or knowledge generation subsystem, as indicators to assess a region's degree of openness (Cooke, 2001). Accordingly, we predict that ***a heterogeneous tacit knowledge base, as a result of immigration, increases the innovation outcome of local and regional production systems.***

To test this hypothesis, we begin in the next section by examining literature pertaining to tacit knowledge flows, followed by a review of research into the geography of knowledge-intensive activities and the role of immigration as a relevant basis for (tacit) knowledge appropriation and creation. After the presentation of the theoretical model and methodology, we summarize the results of the empirical model, applied in the context of autonomous communities in Spain using a multi-linear regression analysis. Finally, we describe the implications of this study, its limitations, and some further research lines.

4.2. Tacit Knowledge

Wartimes are unlike other periods in many ways, including the enhancing effects they have on large, government-led R&D projects, mostly focused on arms and weapons technology. For example, according to some historians, the development of the first atomic bomb helped ensure U.S. victory in the Second World War, then its military supremacy in the following decades. The Manhattan Project alone cost $26 billion (Schwartz, 1998). The race between the United States and Germany to develop the atomic bomb offers an illustrative example of how the joint effort of a diverse team of international researchers supports radical technology advances: The Manhattan Project featured scientists from the United States, Italy, Hungary, the United Kingdom, and Germany, among others. The team was diverse not just from a cultural perspective but also in the represented religious beliefs, genders, and political ideals. The director of the main laboratory in Los Alamos, New Mexico, J. Robert Oppenheimer was Jewish and a political activist with communist ideas—not a particularly popular trait in a capitalist country fighting an ideological battle with communism.

As this famous example indicates, identical R&D projects, built on similar codified knowledge, can produce different results. A diverse tacit knowledge pool can encourage different interpretations and applications of similar codified knowledge, thus increasing the number of innovations that can be applied or exploited in various situations and markets. Immigration creates a diverse tacit knowledge pool that encompasses different societies with varied educational systems, landscapes, languages, political systems, and traditions, shaping members' minds and ways of thinking (Hildrum, 2009). Combining different (tacit) learning approaches is particularly helpful when working on frontiers of knowledge. Obstacles and dead ends are frequent, but thinking successfully about a particular problem, over and over again from different perspectives, can be enabled by different mental schemes working together.

In line with the idea that "we know more than what we can tell" (Michael Polanyi, 1966): 4), human knowledge comprises both codified and tacit forms. The codified form is knowledge that has been written down in codes, formulas, textbooks, and words; it is easier to exchange and develop across distances than is the tacit form (Perraton & Tarrant, 2007). Tacit knowledge instead is interiorized and often cannot be written down, because it is tied to the senses, skills in bodily movement, individual perceptions, physical experiences, rules of thumb, or intuition. They also are complementary knowledge types (Bathelt, et al., 2004; Michael Polanyi, 1966). Polanyi (1966) describes explicit knowledge as worthless without a tacit complement; a new driver can learn how an automobile functions and the rules of the road from a textbook, but those lessons will not produce a good driver. The assistance of an experienced instructor is always required to transfer the tacit, practical knowledge of how to drive, avoid dangers, and deal with traffic.

This complementarity is a critical factor for understanding why innovation activities tend to concentrate in certain regions (Lundvall, et al., 2002) and innovation policies are managed by regional authorities (Uyarra, 2010). Despite global trends, research groups and research activity tend to concentrate geographically. Multinational firms might spread their operations all over the globe, but they often focus their research activity in one place (Carlsson, 2006). Because of the difficulty of transferring tacit knowledge through methods other than working together, this knowledge is very sensitive to distance (Lundvall, et al., 2002). For these reasons, both codified and tacit knowledge evolve together in geographically bounded areas. Even if R&D is being performed in more countries, within these nations, science activities tend to concentrate in a few regions (Lorentzen, 2009).

In addition to their complementary link, we note that in some cases, tacit knowledge may be codifiable, but it usually remains tacit due to the high costs of writing it down or because no dispute motivates the effort to codify it (e.g., if everyone in an organization accepts common procedures and structures for dealing with customer requests (Cohen & Steinmueller, 2000; Cowan et al, 2000). That is, tacit knowledge includes both codifiable and non-codifiable knowledge. The former can be codified but this is not very likely, unless a dispute arrives.

The process of codifying knowledge also leaves fewer resources for the creation of new knowledge. For example, a person working to identify and codify tacit knowledge is left no time and resources to discover new knowledge that would increase the stock of codified and tacit knowledge in the organization. This implication is particularly pertinent in sectors that are developing very quickly, such as the IT industry. Since developments in the high-tech industry are so dynamic, actors in this sector often lack the time needed to codify the extant tacit knowledge. For example, in Silicon Valley hiring personnel from competitors is an essential tactic to acquire new knowledge (Streitfeld, 2014), and in Europe, telecom companies often access innovations by offering venture capital to start-ups and entrepreneurs (Bernau, 2014). In contrast, in other sectors such as automotive or pharmaceutical industries, ideas for innovations usually are developed within a single company or in collaboration with specific suppliers, mainly using codified knowledge. Although such transferable codified knowledge makes it more accessible to firms and formal collaborations, it may also be more accessible to potential competitors than tacit knowledge.

In addition, tacit knowledge may be hard to codify, such as when a researcher has accumulated knowledge about experimental procedures through trial and error. Tacit knowledge is also a personal attribute, which makes it hard to communicate or transfer in any way other than by working together over long periods (Lundvall, et al., 2002). For example, Japanese researchers from the University of Kinki in Osaka have developed a sense for critical times in the process of raising tuna fish in fish farms. This sense or feeling has built up over decades of research on the topic, and only by working together with Japanese scientists were European researchers able to make progress in their effort to develop and raise their own Mediterranean tuna (Sentker, 2013).

Special competences also are needed to integrate codified and tacit knowledge in the effort to produce innovations (Malerba & Orsenigo, 2000a; Parrilli, 2012). Competences relate directly to tacit knowledge, because they increase in importance with the involvement of more tacit knowledge. A key example is the competence needed to work successfully in a team. Since tacit knowledge can be shared only by working together, more competences are needed to be able to transfer and develop it (Malerba & Orsenigo, 2000a).

In terms of its outcomes, the importance of tacit knowledge is widely acknowledged in the literature on regional innovation systems (e.g., Lorentzen (2009). Economic development can be spurred by bringing together agents of regional knowledge exploration subsystems (e.g., universities, research centers) with agents of knowledge exploitation subsystems (firms). Some knowledge pool is embedded in the region. Yet product and process innovations often result from research at the frontier of knowledge, which is also tacit (Haruyama, 2009; Michael Polanyi, 1966), such as raising tuna in fish farms. Research is also the result of trial-and-error processes, in which a critical feeling develops through this process, which constitutes tacit knowledge (Von Krogh, et al., 2000). As Professor Manabu Seoka (hired by the European laboratory from the University of Kinki) described in chapter 3.3, he earned a feeling for critical times through years raising Blue fin tuna in tanks. He closely monitored them, day and night, and adjusted the oxygen, artificial light, and food levels in a delicate and changing balance that he tacitly identifies (Sentker, 2013).

Similarly, the balanced proportions of codified and tacit knowledge differ according to the knowledge specialization and the pace of technology change. Geographical concentration is greater in industries that rely on symbolic knowledge (Asheim, 2007), such as creative industries (Lazzaretti & Parrilli, 2012), because they demand large proportions of tacit knowledge. The focal knowledge in these industries is tied less to formal qualifications or codified knowledge bases and more to the creation of meaning in a specific context (Asheim, 2007). Rapid technology changes also increase the proportion of tacit knowledge, because they reduce the time available to encode tacit knowledge (Cohen & Steinmueller, 2000). In such situations, face-to-face meetings, personal teaching or training, personnel mobility, and acquisition of new personnel become important means to transfer knowledge (Orsenigo, 2000).

The proportions of codified and tacit knowledge not only differ from sector to sector but also evolve and grow (Nonaka & Krogh, 2009). As globalization and ICT developments have increased accessibility to codified knowledge, tacit knowledge needed to evolve accordingly in terms of diversity, to avoid both lock-in from too much codification (Arrow, 1974) and decreased competitiveness due to the non-rivalrous character of codified knowledge (Romer, 1990). Excessive path dependency might in fact hinder the development of new emerging sectors and stall an economy in obsolete procedures.

Different actors that operate in the same region tend to exhibit more similar tacit knowledge vis-a-vis entities in other regions. They share the same context, which shapes their commitment, involvement, and action (Nonaka & Takeuchi, 1994). The technical elements of their tacit knowledge (e.g. skills) become more similar, because they respond to the same regional challenges and problems, thus help to develop similar competences. For example, Acemoglu and Robinson (2012) describe how historic events shape the skills and organization of societies: Spanish colonists encountered hierarchical societies in southern America, unlike the English colonists in the north, and those traits became decisive in the subsequent configuration of the merchant features and skills of these societies. The hierarchically organized societies supported the organization of extractive political and economic systems in Latin America, which hindered the development of a merchant class. Such tendencies produce more similar mental models within specific regions.

If a regional society never interacts with other regions, it thus is likely to suffer lock-in processes with regard to its knowledge and skills. Yet varied, tacit knowledge pools strongly influence the quality of tacit knowledge in an organization (Nonaka & Takeuchi, 1994). If a member of an organization performs only routine operations, her or his tacit knowledge decreases over time (Nonaka & Takeuchi, 1994), thus minimizing the variety of tacit knowledge held by the organization. As a result, it also affects the variety of tacit knowledge available in the region. To avoid lock-in, a closed society would need to exploit different tacit knowledge pools available within the region, such as by increasing the inclusiveness of the labor market or the labor market flexibility. Greater participation by all members of the society (e.g., women, young people) might introduce new tacit knowledge pools to companies and organizations, leading to greater social variety and a more innovative economy. Alternatively, immigrants may represent a source of diversified tacit (and often also codified) knowledge, which might enrich the regional production system.

International migration is not only about bringing skills but also about bringing knowledge and capital (Williams, 2009). All migrants are knowledgeable, not only the highly skilled since "all migration flow involve knowledge transactions between regions" ((Williams, 2009): 311), that are not exclusive to high-tech regions. For instance, migrants need to pay for transports, they may be migrants with some seed capital due to the selection process from immigration policies, with remittances they create business relations with their home region, their investment decisions impact on housing and rejuvenate abandoned districts. Migrants are more likely to become entrepreneurs creating jobs and services to ethnic communities. They also provide services to highly skilled workers of their ethnic community that increase the attractiveness of the region. Low skilled people might even rejuvenate sectors that are being abandoned by the indigenous people.

Via social capital and cultural diversity migrants contribute by making the region more creative (Florida, 2006). They do so through enfolded mobility (Williams, 2009), networks of individual motilities' that produce enduring connections in space in time. These enfolded motilities' include discovery mobility, i.e. short duration mobility such as from students or au-pairs, accompanying mobility, often spouses, children or grandparents following the lead migrant, servicing mobility, the response to the demands created by highly skilled workers, visiting friends and relations mobility, that provide important emotional support and often services at zero cost (such as the mother who visits and takes care of the children) and post-employment mobility, i.e. retirement mobility. These enfolded mobility's intensify the relationships in the regions of Europe and enable the skills and tacit knowledge transfers from region to region, and from tacit knowledge to tacit knowledge inside the region. Tacit knowledge can be distinguished into four forms including embrained, embodied encultured and embedded knowledge (Blackler, 1995). The last two knowledge types are place specific and are, on the one hand, shared understandings arising from socialization and acculturation, and, on the other, shared knowledge that is generated in particular language systems, (organizational) cultures and (work) groups. This social capital can be bridged over to the rest of the indigenous social capital available in the regions, thus helping to create something new. Tacit knowledge available in the region becomes more heterogeneous and valuable. In addition, a too homogenous social capital (bonding) might have negative effects if the society becomes very introverted (e.g. Nazi Germany). Diversity strengthens social capital if their tacit knowledge is shared and bridged over to the rest of the social capitals of the region.

On these bases, we argue that immigration is a critical resource for acquiring relevant tacit knowledge pools. Together with an elevated stock of codified knowledge, diverse tacit knowledge creates unique advantages that are difficult to copy or transfer to other regions. It secures specific, knowledge-based competitiveness, while also reducing the risk of path dependency. In the next section, we discuss the notion of geography-based knowledge and the role of openness as a means to increase creativeness.

4.3. Regionalization of Knowledge and the role of Openness

Innovations in creative industries are based on symbolic knowledge (Asheim, 2007) and large proportions of tacit knowledge. Therefore, these activities exhibit high geographic concentration. Econometric studies confirm that in creative industries, high concentration rates appear, especially in large cities, such that about half of all U.K. creative industry employees are in the Greater London area (DCMS, 2001), and in Spain, 75% are employed in Barcelona and Madrid (Lazzaretti & Parrilli, 2012). Empirical studies also show that knowledge-intensive activities, which are needed to encourage firm innovations, exhibit a similar geographic pattern (Maskell, 1999). The reason might be that collaborative activities are intrinsic to innovation, which requires a multiplicity of actors (Porter, 1998). With the growing complexity of technology, most technological information sources also originate outside any single firm (Chesbrough, 2003). The key interactions among industries, universities, research labs, and consultancies take place at regional levels (Uyarra, 2010), prompting the development of a specialized literature stream on regional innovation systems (RIS), defined as the systematic interaction of a production structure (knowledge exploitation subsystem) with a support infrastructure (knowledge exploration subsystem) through interactive learning processes (Cooke, 1992). According to Lorentzen (2009), RIS literature builds on tacit knowledge and its transfer as central concepts, and it conceives of the region as a source of growth and competitiveness, due to local inherited competences and the local interplay of institutions.

When industries mature, the codification of knowledge increases (Haruyama, 2009), and they become more geographically dispersed (Audretsch & Feldman, 1996). Therefore, regional policy makers might seek to increase tacit knowledge, as a means to promote new industries or reinvigorate existing ones, as well as establish relations across knowledge networks and places (Lorentzen, 2009). This should enhance the embeddedness of the innovation process in the region, thus the competitive position of the regional economy both improves and becomes more firmly rooted in a difficult-to-transfer knowledge base (John Kay, 1999).

Paradoxically though, such geographical concentrations occur in a context of increased globalization in science activities (Reuters, 2013). Innovations that result from increased regional interactions still need knowledge from global interactions. Thus RIS literature acknowledges that knowledge flows arriving from global knowledge pipelines (GKP) prevent over-embededdness and make regional interactions more valuable (Bathelt, et al., 2004). In turn, GKP literature[18] investigates the conditions in which local and global knowledge is exchanged, the type of knowledge that can be transferred, and the consequences for regional production systems (Parrilli, Nadvi, & Yeung, 2013). In this effort, absorptive capacity, or an organization's ability to identify, assimilate, and exploit external knowledge (Cohen & Levinthal, 1990) is a key concept.

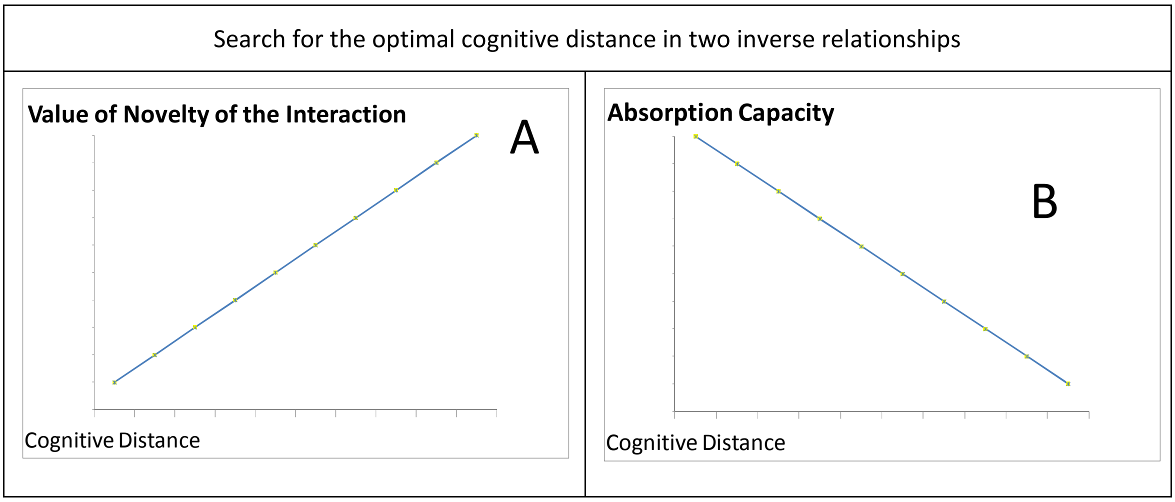
The idea of collaboration implies that the knowledge of collaborating entities should overlap to some degree, to facilitate their mutual understanding. Nevertheless, non-overlapping knowledge is also necessary, to ensure valuable novelty (Nooteboom, 2007). The effort to determine the optimal cognitive distance between two collaborating agents — defined according to differences in their technological knowledge capital (Nooteboom, 2007) — led to the formulation of the proximity paradox ((R. Boschma & Broekel, 2009): 14): "While (cognitive) proximity may be a crucial driver for agents to connect and exchange knowledge, too much proximity between these agents on any of the dimensions (note: social, institutional, cognitive) might harm their innovative performance." In business collaboration, some overlapping is necessary to understand each other's business, but each company needs to bring in knowledge new to the counterpart. If the companies participating in the innovation collaboration are for instance from different sectors, novelty of innovation might have a higher impact but potential failure might also be higher.

Technological capital, defined as the improvement in the instructions for mixing together raw materials ((Romer, 1990): 72), reflects the idea that learning is cumulative, resulting from the knowledge gathered as a result of engaging in trial and error, experimentation, refinement and R&D activities (Cohen & Levinthal, 1990; Romer, 1990). Technology change provides the incentive for capital accumulation. Together, they are responsible for almost all ameliorations in productivity (Romer, 1990). Cumulative R&D (e.g., patents) increases technological capital, cognitive proximity, and the absorptive capacity of the firm. By definition, absorptive capacity always increases novelty (Cohen & Levinthal, 1990). Yet

18 These pipelines also have been referred to as global value chains, global production networks, or global innovation networks.

Nooteboom (2007) provides clear evidence that the *effect of novelty value* decreases with higher cognitive proximity. That is, there is a greater risk of failure in projects with higher cognitive distance, but eventually successful projects have a greater impact in terms of their novelty value. Thus, there is a positive effect of cognitive distance, because firms can take bigger steps if they collaborate with firms positioned at a certain cognitive distance. This observation was the basis for Boschma & Broekel (2009) proximity paradox, which indicates the need to find an optimal cognitive distance to both increased absorptive capacity through adequate proximity, and enhanced novelty value through sufficient cognitive distance (see Figure 4.1).

Figure 4.1: Absorption Capacity and Cognitive Distance



With this study, we seek to fine-tune this approximation by differentiating codified and tacit knowledge. Rather than finding an appropriate cognitive distance as the intersection of two inverse relationships - (B) the higher the cognitive distance, the lower the absorptive capacity and (A) the higher the cognitive distance, the higher the value of novelty of the cooperation - we propose that codified and tacit knowledge follow different paths and slopes, such that cognitive proximity should be particularly relevant for codified knowledge, but cognitive distance is more critical for tacit knowledge. Heterogeneity of knowledge thus is particularly relevant in the latter case, but homogeneity should be particularly relevant in the former.

Specifically, we posit that cognitive proximity in codified knowledge (homogeneity) increases absorptive capacity, enabling the exchange of knowledge with agents all over the world and lowering coordination costs (e.g., fewer coordination meetings are required). That is, codified knowledge can be shared over long distances and creates opportunities to collaborate with a wide range of partners.

However, these traits might also increase coordination costs. To minimize these coordination costs, the focus should be on increasing absorptive capacity, even if that reduces the novelty value of the interaction. Thus, we predict a steeper relationship between cognitive distance and absorptive capacity, and a flatter relationship between cognitive distance and value of novelty when we isolate codified knowledge from tacit knowledge. Any reduction in the cognitive distance of the codified knowledge alone (higher cognitive proximity) leads to higher absorptive capacity, because the codified knowledge can be exchanged regionally, nationally, or internationally. Therefore, increases in cognitive proximity in codified knowledge results in a larger increases in absorptive capacity than if we included both knowledge types (R. Boschma & Broekel, 2009; Nooteboom, 2007).

Moreover, with reduced cognitive distance, the number of potential collaborative agents increases as more can be accessed for collaboration, broadening the knowledge base (Cohen & Levinthal, 1990), which may further increase codified knowledge and absorptive capacity.

In contrast, cognitive distance (heterogeneity) is more important for increasing the novelty value of tacit knowledge. Since the exchange of tacit knowledge is geographically bounded, possible transaction difficulties (e.g., due to misunderstandings) occur in geographical proximity. Costs of meetings to overcome these transaction difficulties are minimal. Any problem that arises can be solved by calling up a short meeting.

We may consider two different companies that collocate in the same industrial district, an aeronautical company and a company that produces bicycles. An innovation project of these two companies might end in novel innovations for both. But due to the different industry culture of the company and the differences of the value chains and clients, among other features, there might be misunderstandings in concepts and working methods that require more meetings to solve and share tacit knowledge. Since they co-locate, transaction costs to share this tacit knowledge are minimized.

Consider Eimal, an Afghan refugee in Germany who has worked as aeromechanic in Kabul and works now as bicycle mechanic in Dresden (Rudzio, 2015). As part of an enfolded community, his uncle lives in Bochum running an automotive repair shop, he can bridge his tacit knowledge together with his skills that is likely to lead to novel innovations in the bicycle workshop in Germany. At the same time, there are many hurdles that need to be taken that are common sense to indigenous people. When working with his colleagues and clients, Eimals classification for urgency, and customer convenience might lead to many misunderstandings that can only be solved by trial and error.

This trial and error process is solved on the spot with lower costs than if the project was developed by working across large distance. Therefore, the relationship between cognitive distance and novelty value is steeper when we consider tacit knowledge alone. Potential novel combinations of tacit knowledge bases might lead to creative solutions and innovations, but problems due to misunderstandings also arise failing short on what would be obvious for indigenous people, such as the rituals in the interaction with each other.

Nevertheless, what would constitute a failure of an innovation project at distance can be solved immediately at low cost when working physically together. The increase in cognitive distance also increases the novelty value of cooperation, because tacit knowledge is exchanged mostly regionally, which lowers coordination costs. The frequent exchanges among these collaborating agents vastly increase the novelty value of the interaction, whereas any reduction of cognitive distance results in smaller increases of absorptive capacity when compared to codified knowledge. Eimal needs to learn obvious things that go far beyond the language skills alone. But it’s worth the hurdles, because what he has to offer may lead to novel innovation and what would lead to a failure at distance are hooks that can be solved more easily in physical proximity.

Our model thus proposes a differentiated approach to identifying the most appropriate cognitive distance to attain both a good absorptive capacity and a relevant novelty value. In Table 4.1, we compare the possible consequences of deviations from the optimal cognitive distance and its solutions, according to two models: 1) Broekel and Boschma (2009), and 2) our model in chapter 2.5. Broekel and Boschma prescribe the same solution for any suboptimal cognitive distance, namely, the importance of achieving a common knowledge base with diverse but complementary capabilities. Instead, we recommend focusing on homogeneity for codified knowledge improvements and heterogeneity for tacit knowledge upgrades.

Table 4.1: Cognitive proximity and knowledge bases

Cognitive Proximity	Too Much Proximity	Too Little Proximity	Solutions: Broekel and Boschma	Our Solution:
Codified Knowledge	Lack of novelty	Misunderstanding due to missing common knowledge	Common knowledge base with diverse but complementary capabilities	Focus on homogeneity in the codified knowledge base
Tacit Knowledge	Lack of novelty	Misunderstanding due to missing common knowledge		Focus on heterogeneity in the tacit knowledge base

4.4. Empirical Methodology

In this section, we outline the results of our empirical analysis. The objective is to test our core hypothesis whether immigration per se is beneficial for innovation activity. Through immigration, tacit knowledge from skills but also tacit knowledge arriving in the region through bridging from enfolded communities mingles with tacit knowledge and social capital available in the region. Through bonding (within the community) and bridging (between the communities) cognitive distance increases in the region and positively influences the regional innovation performance. To test the hypothesis, we investigated 174 indicators in three categories over a five-year period (2008–2012). The first category pools migration variables that indicate tacit knowledge conveying into the region. The second category is an indicator for codified knowledge stock in the region and the third category provides information on innovation results:

1. Migration variables

2. R&D and investment variables
3. Innovation results variables

We gathered data from the Spanish national statistics office (Instituto Nacional de Estadística [INE]) and the European office (Eurostat). These institutions provided data about 17 autonomous communities in Spain, including 31 different indicators in 2008 and 2009 spanning all three categories; 38 indicators in 2010; and 37 indicators for the years 2011 and 2012. In particular, INE provided, since 2010, data about labor mobility, which explains the increase in the number of indicators in the last three years (2010–2012). Table 4.2 contains an overview of the different indicators we used.[19]

19 Indicators in red are subject to further analysis, after we reduced the list to 17 indicators, using a process that we describe subsequently.

Table 4.2: List of indicators used to perform the analysis

		2008 & 2009	2010 & 2011 & 2012
Migration	Total internal migration in percentage	X	X
	Internal migration of foreigners in percentage	X	X
	Internal migration of Spaniards in percentage	X	X
	Migration from outside Spain in percentage (MOS)	**X**	**X**
	Balance of total external migrations in percentage	X	X
	Variations in registrations in percentage	X	X
	Internal regional migration excl intra-regional migration in percentage	X	X
	Population born outside the region in percentage (PBOR)	**X**	**X**
	Population born outside the province in percentage	X	X
	Population born outside Spain in percentage (PBOS)	**X**	**X**
	Foreigners with residency in percentage (FR)	**X**	**X**
	Variations of foreigners in percentage	X	X
	Foreigners in regions in percentage (FREG)	**X**	**X**
	Foreign students in percentage (FSTUD)	**X**	
	Population change in percentage	X	X
	Locally mobile employees with 3 to 5 years of residency in percent		X
	Locally mobile employees with more than 5 years of residency in percent (LME)		X
	Regionally mobile employees with 1 or less years of residency in percent		X
	Regionally mobile employees with 1 to 3 years of residency in percent		X
	Regionally mobile employees with 3 to 5 years of residency in percent		X
	Regionally mobile employees with more than 5 years of residency in percent (RME)		X
R&D and investment	**R&D investment per capita (RD)**	**X**	**X**
	Spending on R&D personnel per capita (RDPER)	**X**	**X**
	Investments on full-time researchers per capita (RES)	**X**	**X**
	R&D investment from businesses per capita	X	X
	Spending on R&D personnel from business per capita	X	X
	Spending on researchers from business per capita	X	X
	Tertiary education in percent (TEDU)	**X**	**X**
	Businesses with activities in innovation in percent (BI)	**X**	**X**
	Innovative businesses (EIN) in percent of all businesses	X	X
	Employment in high tech sectors in percent (EMPHT)	**X**	**X**
Innovation results	**Patent applications per capita (PAT)**	**X**	**X**
	High-tech patent applications per capita	X	
	Not-patented inventions per capita[1] (INV)	**X**	**X**
	Industrial design applications per capita (DES)	**X**	**X**
	Trade mark applications per capita (TRD)	**X**	**X**
	Business names applications per capita (BNS)	**X**	**X**

An available Migration Filter provides information about openness to migration according to 15 indicators in 2008 and 2009 and 22 indicators in 2010–2012. According to Maskell et al. (2006) and Van Dijk (Van Djik, 2000), internal and external migration, census turnover (registrations), and mobility indicators provide key information about the availability, flow, and creation of tacit knowledge. Williams (2007b) research centered on knowledge transfer of migrants and concluded that migrants are significant actors especially there, where borders constitute substantial economic and cultural barriers. Tacit knowledge is encapsulated in the individual and are transported by the migrants into the region through enfolded mobilities

(Williams, 2009), which are based on networks producing enduring connections accross space and people.

This new tacit knowledge entering the region is than shared through socialization in the case of tacit to tacit knowledge transfer, or externalized in the case of tacit to codified knowledge transformation (I. Nonaka, Toyama, & Konno, 2000). This tacit knowledge rooted in action, procedures, routines, commitment, ideas values and emotions are held by any migrant not only by highly qualified personnel (Williams, 2007b). Therefore, variables including *Migrants from outside Spain*, *Population born outside Spain*, *Foreigners with residency* or *Foreign Students* provide information on new tacit knowledge entering the region. The latter bring in tacit knowledge but absorb mainly codified knowledge from the region.

The learning region transmits this tacit knowledge available through face-to-face interaction, but also tacit knowledge is shared and produced inside the firms (Gertler, 2003). Therefore, tacit knowledge can be shared by geographical and relational proximity. For instance, the production, appropriation and flow of tacit knowledge occur by means of people working closely together on a specific subject (Cohendet et al, 2000). Individuals can transfer this type of knowledge by changing jobs in a new organizational environment. Therefore, high labor flexibility is a sign of high tacit knowledge flow, here measured through the variables local mobile employees and regional mobile employees.

In this context, Denmark is frequently cited for having a highly flexible, mobile labor market that permits the exchange of tacit knowledge, such that it specializes in the DUI innovation mode (based on learning-by-Doing, by-Using, and by-Interacting) mode. This mode relies on processes of interactive learning and experience-based know-how (Jensen, et al., 2007), which help transferring knowledge from one firm to another. In our model, the indicators that provide evidence on the heterogeneity of tacit knowledge bases are direct internal and external migration flows. Indicators of the percentage of the population born outside the region and country also provide information about past migration.

Thus, these variables indicate the level of cognitive distance of tacit knowledge in the region, obtained from bringing in new tacit knowledge from outside the RIS. Immigrants augment cognitive distance in a region by introducing different sets of values, points of view, and forms of action. Hunt and Gauthier-Loiselle (2008) show that immigration lead to higher patents in the region, while Saxenian (2002b) shows how immigration sparks entrepreneurship in a region.

In our model, we measure this effect at various geographical levels (e.g., outside Spain, outside the region, outside the province, local mobility) with the objective of testing if different levels of immigration have an effect on the type of knowledge brought into the region. In line with the theory exposed, local migration would contribute more with codified rather than tacit knowledge.

A second set of indicators provide information about the available codified knowledge stock in the region, which augments collaboration capacity by reducing cognitive distance to other codified knowledge pools that might exist inside and outside the region. These indicators include R&D investment, spending on R&D personnel and full-time researchers, private-sector involvement in R&D, tertiary education, and employment in high-tech sectors.

Cowan et al (2000) distinguished codified knowledge from tacit knowledge in a system of two axes, where didactic instruction, textbooks, grammars and dictionaries, manuals, and the like are the most codified form of knowledge. The variable *tertiary education* therefore indicates codified knowledge stock increase. *R&D investment, R&D personnel, full-time researchers,* or *employment in high-tech sectors* is also often mentioned as a form of measuring stock of codified knowledge since this variable is more linked to theoretical learning (Gertler, 2003), which is acquired through codified forms of knowledge. The boundaries though of codified and tacit knowledge are in a flux and some research might also involve tacit knowledge. Likewise, migrants might bring codified knowledge into the region (Cowan et al, 2000). While a clear distinction is not possible, the fact that we do not discriminate migrants for instance according to their level of education in most of the variables selected, is an approach to measure tacit knowledge brought by them into the region.

Research may aim at transforming tacit elements of knowledge into codified forms (Lundvall, et al., 2002). For instance, Lundvall et al (2002) distinguished individual knowledge into 4 different types of knowledge according to their degree of codification. The most codified form of knowledge has the 'know-what' form, which is knowledge about facts. The second type of knowledge, the 'know-why' form, is also easy to codify and refers to knowledge about principles and laws of motion in nature, in the human mind and in society. These two types of knowledge are largely important in science based areas, which is largely codified.

The regression analysis also includes 3 control variables: GDP per capita, Population and Population Density. The selection of the variables are based on the Jacobs externalities that cities due to their diversification in close proximity achieve higher innovations and growth (Jacobs, 1969). The selection of GDP per capita is based on the idea that people could base their decision to migrate on the wealth of a region or that high GDP per capita allows better funding for Research in the companies and public entities that leads to better innovation results.

The innovation output is measured by six indicators (five in 2010–2012): patent application per capita (PAT), high-tech patent applications (2008 and 2009 only), not-patented inventions used in companies (INV), industrial design applications (DES), trademark applications (TRD), and business name applications (BNS). Patent applications and high-tech patent applications are outcomes that relate closely to codified knowledge; industrial design applications and trademark applications relate more to tacit knowledge. Not-patented inventions used in companies and business name applications could be related to either form of knowledge or both. We purposefully consider this mixture of innovation outputs in an attempt to avoid the controversy surrounding the use of patent applications as proxies for innovation outputs, because not all industrial sectors patent similarly, not all patents lead to true innovations, and not all patents produce short-term economic returns (Rodríguez-Pose & Comptour, 2012).

4.4.1. Main determinants of innovation results

We analyzed all data for the years 2008–2012 of all 17 Spanish regions to select the six most relevant indicators for the Migration Filter. Another six indicators constitute the R&D Filter. These filters represent the independent variables we use to test our hypothesis. We also included three control variables: gross domestic product (GDP) per capita, population, and population density (i.e., population/km^2). The most relevant indicators are those that reveal variety in their type but also correlate with the innovation output variable. Some indicators measured nearly the same, for instance regional mobility with 3 and with 5 years of residency. Therefore, in these cases only one indicator was selected.

4.4.2. Results: Basic Correlations

The series of three years allows us to analyze panel data, since only in the series of three years all indicators were available. In Tables 4.3–4.7, we detail the calculated correlations and *p*-values.[20] By selecting the most important indicators, we facilitate the interpretation of the results. Values in red in these tables are significant at $p < .10$.

Table 4.3: Correlation and significance of selected indicators, 2008

2008	4. MOS	8. PBOR	10. PBOS	11. FR	13. FREG	14. FSTUD	1. RD	2. RDPER	3. RES	7. TEDU	8. BI	10. EMPHT
1. PAT	**0.48 .**	**0.51 ***	0.33	0.40	0.30	**0.63 ****	**0.74 *****	**0.83 *****	**0.83 *****	**0.61 ****	**0.59 ***	0.39
3. INV	**0.46 .**	**0.46 .**	**0.41 .**	**0.49 ***	0.38	**0.52 ***	**0.59 ***	**0.70 ****	**0.68 ****	**0.41 .**	**0.67 ****	0.20
4. DES	0.40	**0.43 .**	**0.57 ***	**0.56 ***	**0.56 ***	-0.04	0.13	0.13	0.06	0.09	**0.48 .**	0.00
5. TRD	0.61	**0.72 *****	**0.55 ***	**0.50 ***	**0.56 ***	**0.61 ****	**0.71 *****	**0.70 ****	**0.63 ****	**0.58 ***	0.39	**0.69 ****
6. BNS	0.48 *	0.25	0.57 *	0.52 *	0.58 *	0.10	0.08	0.12	0.12	-0.03	-0.06	0.28

. $p < .1$. * $p = [.1–.05]$. ** $p < .05$. *** $p < .01$.

Table 4.4: Correlation and significance of selected indicators, 2009

2009	4. MOS	8. PBOR	10. PBOS	11. FR	13. FREG	14. FSTUD	1. RD	2. RDPER	3. RES	7. TEDU	8. BI	10. EMPHT
1. PAT	0.35	**0.47 .**	0.36	0.41	0.28	**0.6 ****	**0.73 *****	**0.81 *****	**0.82 *****	**0.58 ***	**0.58 ***	0.38
3. INV	0.40	**0.44 .**	0.40	**0.44 .**	0.32	**0.55 ***	**0.53 ***	**0.62 ****	**0.62 ****	0.37	**0.57 ***	0.27
4. DES	**0.47 .**	0.40	**0.62 ****	**0.64 ****	**0.61 ****	-0.01	0.01	0.07	0.04	0.07	0.26	0.15

[20] The complete list of correlations can be found in the annex.

5. TRD	0.54 *	0.65 **	0.52 *	0.50 *	0.5 *	0.57 *	0.58 *	0.58 *	0.53 *	0.55 *	0.40	0.73 ***
6. BNS	0.40	0.35	0.41 .	0.39	0.44 .	0.07	0.01	0.00	-0.02	0.18	0.05	0.44 .

. *p* < .1. * *p* = [.1–.05]. ** *p* < .05. *** *p* < .01.

Table 4.5: Correlation and significance of selected indicators, 2010

2010	4. MOS	8. PBOR	10. PBOS	11. FR	17. LME	21. RME	1. RD	2. RDPER	3. RES	7. TEDU	8. BI	10. EMPHT
1. PAT	0.23	0.37	0.20	0.24	0.55 *	0.44 .	0.72 **	0.80 ***	0.81 ***	0.66 **	0.60 *	0.42 .
2. INV	0.35	0.38	0.27	0.26	0.5 *	0.34	0.69 **	0.77 ***	0.78 ***	0.53 *	0.48 .	0.38
3. DES	0.49 *	0.30	0.57 **	0.44 .	0.16	0.36	0.13	0.25	0.23	0.17	0.30	0.15
4. TRD	0.62 **	0.66 **	0.51 *	0.46 .	0.47 .	0.68 **	0.59 *	0.63 **	0.57 *	0.56 *	0.38	0.80 ***
5. BNS	0.47 .	0.41 .	0.41 *	0.22	0.09	0.33	0.30	0.26	0.21	0.18	-0.31	0.63 **

. *p* < .1. * *p* = [.1–.05]. ** *p* < .05. *** *p* < .01.

Table 4.6: Correlation and significance of selected indicators, 2011

2011	4. MOS	8. PBOR	10. PBOS	11. FR	17. LME	21. RME	1. RD	2. RDPER	3. RES	7. TEDU	8. BI	10. EMPHT
1. PAT	0.16	0.36	0.10	0.10	0.61 **	0.44 .	0.76 ***	0.83 ***	0.85 ***	0.73 **	0.74 **	0.48 .
2. INV	0.20	0.22	0.16	0.11	0.54 *	0.32	0.68 **	0.76 ***	0.76 **	0.51 *	0.67 **	0.31
3. DES	0.71 **	0.30	0.82 ***	0.64 **	-0.10	0.27	0.01	0.08	0.10	-0.12	0.16	0.09
4. TRD	0.57	0.6 .	0.48 *	0.44 .	0.59 **	0.68 **	0.53 *	0.57 *	0.53 *	0.5 *	0.57 *	0.66 **
5. BNS	0.49 *	0.35	0.39	0.23	0.16	0.36	0.21	0.17	0.13	0.18	0.09	0.47 .

. *p* < .1. * *p* = [.1–.05]. ** *p* < .05. *** *p* < .01.

Table 4.7: Correlation and significance of selected indicators, 2012

2012	4. MOS	8. PBOR	10. PBOS	11. FR	17. LME	21. RME	1. RD	2. RDPER	3. RES	7. TEDU	8. BI	10. EMPHT
1. PAT	0.05	0.40	0.20	0.28	0.62 **	0.47 .	0.55 *	0.67 **	0.68 **	0.59 *	0.75 ***	0.41
2. INV	0.08	0.43 .	0.22	0.28	0.46 .	0.40	0.54 *	0.65 **	0.62 **	0.5 *	0.83 ***	0.51 *
3. DES	0.66 **	0.38	0.78 ***	0.71 ***	0.05	0.40	-0.05	0.06	0.07	-0.05	0.35	0.13
4. TRD	0.54 *	0.60 **	0.55 *	0.51 *	0.43 .	0.56 *	0.41 .	0.49 *	0.46 .	0.46 .	0.49 *	0.69 **
5. BNS	0.43 .	0.32	0.42 .	0.33	-0.02	0.32	0.10	0.12	0.07	0.09	0.12	0.37

. *p* < .1. * *p* = [.1–.05]. ** *p* < .05. *** *p* < .01.

Many of the selected indicators thus are highly correlated with at least one innovation result indicator. It can be observed that indicators falling under the R&D category show the highest correlations with output indicators *Patenting Activity, Non-Patented Inventions* and *Trade Marks Applications*. Nevertheless, this category providing the level of codified knowledge stock in the region does not show correlations with *Design Activity* and *Business Names Applications*.

On the other hand the Migration category shows high correlations with *Designs Activity, Trade Marks Applications* and *Business Names Applications*. There are also selective years where the Migration category is highly correlated with *Patenting Activity* and *Non-Patented Inventions*. Nevertheless, correlations cannot be observed for all years nor for all migration indicators. For example, between 2010 and 2012 regional and local mobile employees show higher correlations whereas between 2008 and 2009 correlations are between *People Born Outside the Region* and *Patenting Activity*.

Possible time lags have been analysed. Nevertheless, highest correlations between input and output variables are observed in the same year. After scaling the focal panel data to ensure the comparability of the indicators, we analyzed this scaled data matrix with the principal component analysis (PCA), followed by a regression function.

4.4.3. Principal Component Analysis

The PCA statistical procedure reduces the complexity of the data set (Jolliffe, 2002). It fits an n-dimensional ellipsoid to the data, where each axis of the ellipsoid represents a principal component. The PCA rotates the set of points around their mean to align with the principal components, moving as much of the variance as possible into the first dimensions and dropping those with little variance, with minimum loss of information.

The PCA first selects the ellipsoid with the highest variance, or the first principal component. Then it identifies the data with the second highest variance, with the constraint that it must be uncorrelated with the first component. The higher the variance, the more explanatory the factors in this component are. The projections, in the form of arrows, show the direction of individual indicators and their importance, such that longer arrows signal greater variance and importance.

This dimensionality reduction is useful for visualizing the two knowledge components, tacit and codified, in innovation processes. Moreover, it allows us to perform an individual analysis on each region, since the Autonomous Communities can be visualized along these two axes, i.e. knowledge components. In addition, the principal component analysis leads us to factor analysis, since the latter is considered as its extension. Through factor analysis we are able to describe the covariance relationships among the many variables in terms of few underlying but unobservable factors (Johnson & Wichern, 2007). That is, it enables us to see if variations in 12 observed variables mainly reflect the variations in a few unobserved variables (factors).

The hypothesis is that these few factors are the codified and tacit knowledge factors with whom we would be able to test the accuracy of a regression analysis and compare the calculated value by means of the factors with the real value. Furthermore, it allows us to test it on 5 different equations. By means of graphical support we may draw conclusions not only on the validity of the concept itself, but also - through their position in the graph - on the individual performance or situation of the Autonomous Communities. Another advantage of this methodology is that we are able to draw conclusions about how variables are related to each other within the group. This enables us to understand individual indicators and opens up future research lines in improving the predictability of the factors.

To achieve high innovation outputs in a region, both tacit (Migration Filter) and codified (R&D Filter) knowledge are needed. Although we assess fewer indicators than we started with (six migration, six R&D and investment, and five innovation results) because our panel data span three years: 2010, 2011, and 2012. Some very meaningful indicators are not available in 2008 and 2009, and we had to exclude these from the panel data matrix. We summarize these selected indicators in Table 4.8.

Table 4.8: Variable definitions and data sources

	Migration Filter (2010–2012)	
Migration from outside Spain as a percentage (MOS)	Immigration flow from foreign countries per autonomous community and year	Instituto Nacional de Estadísticas
Population born outside the region as a percentage (PBOR)	Population per autonomous community and place of birth	Instituto Nacional de Estadísticas
Population born outside Spain as a percentage (PBOS)	Population per province and place of birth	Instituto Nacional de Estadísticas
Foreigners with residency as a percentage (FR)	Population per country and place of birth	Instituto Nacional de Estadísticas
Locally mobile employees with more than 5 years of residency as a percentage (LME)	Occupied persons per municipality and time of residency in the municipality	Instituto Nacional de Estadísticas
Regionally mobile employees with more than 5 years of residency as a percentage (RME)	Occupied persons per autonomous community and time of residency in the municipality	Instituto Nacional de Estadísticas
	R&D Filter (2010–2012)	
R&D investment per capita (RD)	Total internal spending in R&D per capita and autonomous community	Instituto Nacional de Estadísticas
Spending on R&D personnel per capita (RDPER)	Total internal spending in R&D per capita and autonomous community.	Instituto Nacional de Estadísticas
Investments in full-time researchers per capita (RES)	Spending on investigators employed on a full time basis per capita.	Instituto Nacional de Estadísticas
Tertiary education as a percentage (TEDU)	Persons aged 25–64 years with tertiary education attainment by NUTS 2 level (%)	Eurostat
Businesses with activities in innovation as a percentage (BI)	Businesses with innovation activity per autonomous community	Instituto Nacional de Estadísticas
Employment in high tech sectors as a percentage (EMPHT)	Employment in technology and knowledge-intensive sectors by NUTS 2 regions	Eurostat
Variable	**Dependent Variable (2010–2012)**	**Definition Sources**
Patents per capita (PAT)	Patent applications per capita per autonomous community and year	Instituto Nacional de Estadística (INE), Oficina Española de Patentes y Marcas (OEPM). Estadísticas de Propiedad Industrial
Not-patented inventions per capita (INV)	Utility model applications per capita per origin and year	Instituto Nacional de Estadística (INE), Oficina Española de Patentes y Marcas (OEPM). Estadísticas de Propiedad Industrial
Industrial design applications per capita (DES)	Industrial design applications per capita per origin and year	Instituto Nacional de Estadística (INE), Oficina Española de Patentes y Marcas (OEPM). Estadísticas de Propiedad Industrial
Trademark applications per capita (TRD)	Trademark applications per capita per origin and year	Instituto Nacional de Estadística (INE), Oficina Española de Patentes y Marcas (OEPM). Estadísticas de Propiedad

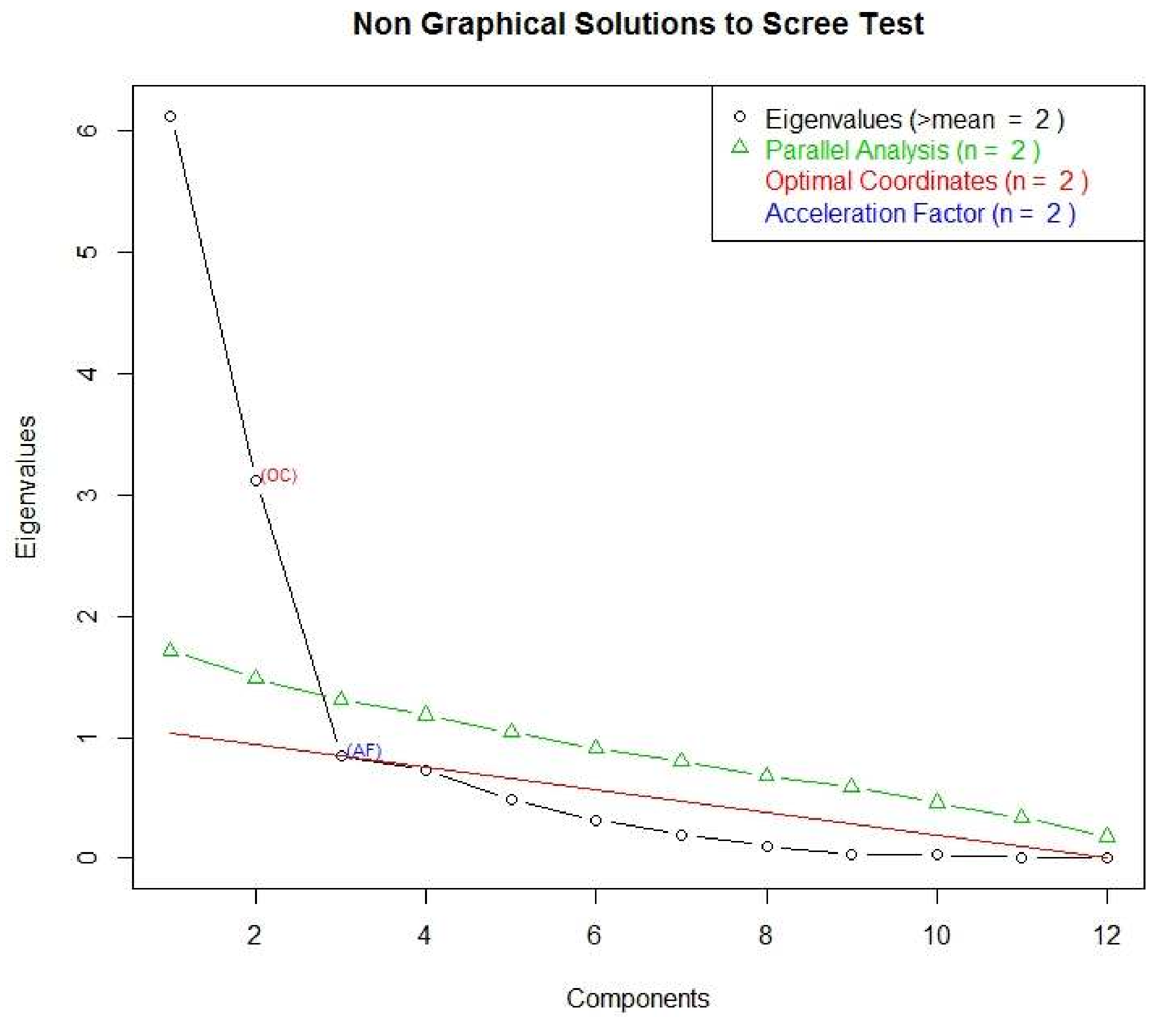
		Industrial
Business name applications per capita (BNS)	Business name applications per capita per origin and year.	Instituto Nacional de Estadística (INE), Oficina Española de Patentes y Marcas (OEPM). Estadísticas de Propiedad Industrial

Variance explains any difference in behavior across the analyzed Spanish regions. Reducing this complexity to two principal components would be sufficient to determine if tacit and codified knowledge indicators represent principal components in the innovation process and if they are uncorrelated. For a set of k variables, each principal component can be defined as follows:

$$(1) \qquad j = \beta_{1j}X_1 + \beta_{2j}X_2 + \cdots + \beta_{kj}X_k,$$

where k are the variables and is the weight that indicates the strength of the association between variable i and principal component j. Thereafter, we must select an adequate number of factors to describe the data. We do so with a scree plot to identify the number of relevant components, as we show in Figure 4.2.

Figure 4.2: Number of factors and their importance



Importance of Components							
	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7
Standard Deviation	2,48	1,77	0,92	0,85	0,70	0,56	0,45
Proportion of Variance	0,51	0,26	0,07	0,06	0,04	0,03	0,02
Cumulative Proportion	0,51	0,77	0,84	0,90	0,94	0,97	0,99
Eigenvalues	6,13	3,12	0,84	0,73	0,49	0,32	0,20

According to the eigenvalues, ordered from largest to smallest, we can determine the appropriate number of components, which occurs at a bend in the plot (Johnson & Wichern, 2007). The bend occurs around component i = 3. This bend is calculated by the Acceleration Factor (AF in Figure 4.2.), which indicates the position where the slope of the curve change abruptly (Raîche, et al., 2006). Therefore, the scree plot test suggest to retain 3 components.

The Kaiser-Guttman rule, only components with eigenvalues higher than 1 should be retained (Component 1: 6.13, component 2: 3.12, component 3: 0.84). Therefore, under this rule only 2 components should be retained. Furthermore, the Parallel analysis is another test to calculate the number of components to retain and is applied on finite components as it is the case here. Here, only components should be retained where the eigenvalues are superior or equal to the average of the eigenvalues (see green line in Figure 4.2). Clearly, only two components should be retained under this analysis.

Observing the proportion of variance in the table underneath Figure 4.2., we can see that after the first two components, the proportion of variance values are relatively small and approximately the same size.[21] Therefore, the first two principal components are sufficient to summarize total sample variance and test our hypothesis.

We analyze first theses components with a variable factor map, see figure 4.3 below, which displays the indicators and their position in the two principal components. The R&D Filter indicators concentrate close to component 1, which explains 51.06% of the variance. Three Migration Filter indicators align close to component 2, which explains 25.98% of the variance. Therefore, the two principal components collectively explain 77.04% of total sample variance. The third component , thus we consider a reduction of the data into two principal components reasonable.

[21] The values are 0,07 for component 3, 0,06 for component 4, 0,04 for component 5, 0,03 for component 6, and 0,02 for component 7.

Figure 4.3: Variable Factor Map: Migration and R&D Filter Indicators

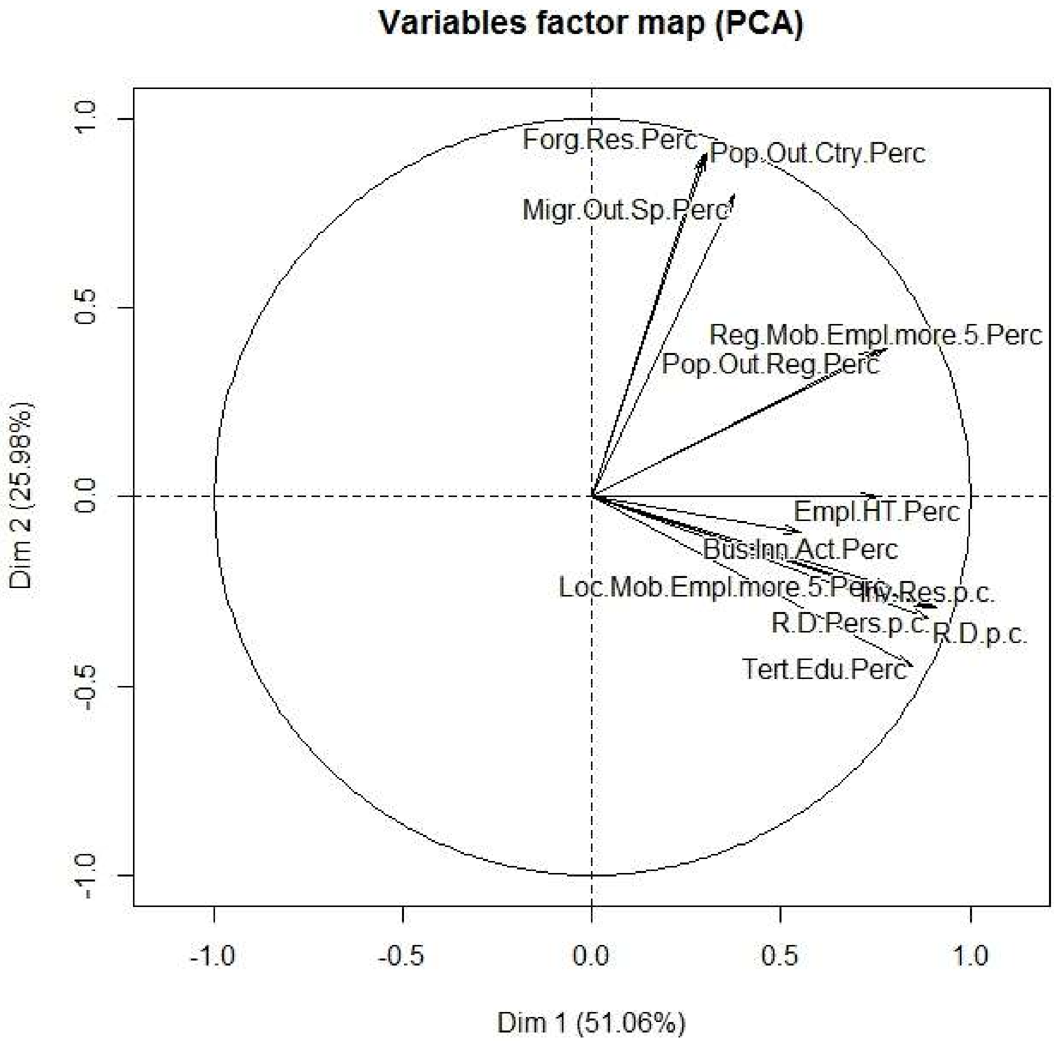
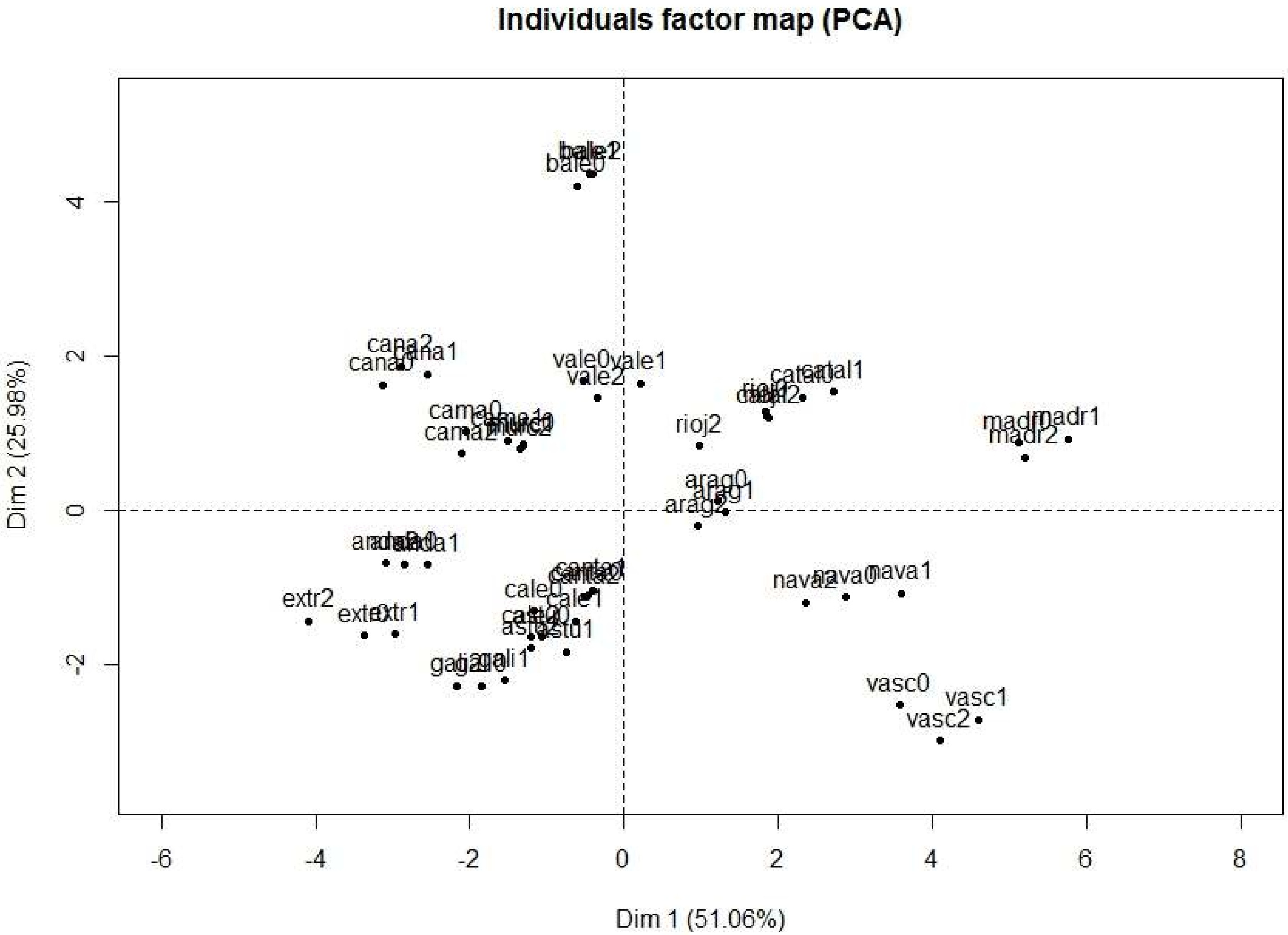


Figure 4.4: Individual Factor Map: Spanish Regions



The individual factor map in figure 4.4 indicates where the regions in Spain locate according to the components. Navarre and the Basque Country locate along the R&D Filter but with below average migrations; Valencia, and Balearic Islands appear along the Migration Filter. Madrid, Aragón, La Rioja and Cataluña both show more balanced proportions, with above average R&D and migrations. The group of regions Extremadura, Castilla y León, Asturias, Galicia, and Cantabria show below average figures on R&D and Migrations. Murcia, Castilla la Mancha and Canary Islands show below average R&D but above average in Migrations.

According to factor analysis, which describes the covariance relationships among two groups of variables, we also find that the initial indicators are associated with both factors, not one factor alone, making it difficult to interpret the results. We summarize these initial factor loadings in Table 4.9.

Table 4.9: Estimated initial loadings of individual Migration and R&D Filter indicators

Indicator	ILC 1*	ILC 2	ILC 3	ILC 4	ILC 5	ILC 6	ILC 7	ILC 8	ILC 9	ILC 10
Migration from outside Spain as a percentage (MOS)	0,152	-0,452	0,164	0,355		0,331	0,570			0,370
Population born outside the region as a percentage (PBOR)	0,314	-0,222	-0,365	-0,332		-0,151	0,399		0,219	-0,556
Population born outside Spain as a percentage (PBOS)	0,122	-0,513	0,130	0,222			-0,161	-0,370	-0,544	-0,379
Foreigners with residency as a percentage (FR)	0,119	-0,512	0,177		-0,111	-0,122	-0,467		0,650	
Locally mobile employees with more than 5 years of residency as a percentage (LME)	0,321	0,136		-0,167	-0,443	0,762	-0,123			-0,180
Regionally mobile employees with more than 5 years of residency as a percentage (RME)	0,303	-0,219	-0,322	-0,465	-0,199	-0,160			-0,365	0,567
R&D investment per capita (RD)	0,359	0,182		0,274		-0,249	0,249	0,307		
Spending on R&D personnel per capita (RDPER)	0,368	0,165		0,269	-0,108	-0,203	-0,115	0,173		
Investments on full-time researchers per capita (RES)	0,361	0,165	0,134	0,271	-0,209	-0,208	-0,180			
Tertiary education as a percentage (TEDU)	0,342	0,253						-0,828	0,258	0,187
Businesses with activities in innovation as a percentage (BI)	0,223		0,721	-0,476	0,401			0,119	-0,115	
Employment in high-tech sectors as a percentage (EMPHT)	0,305		-0,363	0,144	0,716	0,296	-0,358	0,140		
Importance of Components										
Standard deviation	2,475	1,766	0,919	0,852	0,697	0,562	0,446	0,322	0,189	0,166
Proportion of variance**	0,511	0,260	0,070	0,061	0,041	0,026	0,017	0,009	0,003	0,002
Cumulative proportion	0,511	0,770	0,841	0,901	0,942	0,968	0,985	0,993	0,996	0,999
Eigenvalues	6,128	3,118	0,845	0,726	0,486	0,316	0,199	0,104	0,036	0,028

*ILC = Initial Loading Component.

The initial loadings of the Migration Filter show positive values for initial loading component 1 and negative values for initial loading component 2. These bipolar loadings imply that regions with above-average scores on the first factor have below-average scores in the second. The MOS (migration from outside Spain), PBOS (persons born outside Spain), and FR (foreign residents) indicators in particular show significant negative values. The initial loadings of the R&D Filter instead have positive values on both components. Because we cannot separate clearly these loadings, it is difficult to identify their implications; further analysis is needed to draw plausible conclusions.

A possible option here is factor rotation, which rotates axes to determine if each indicator might be associated with only one loading. In Varimax rotation, the initial loading matrix is rotated by multiplying it by an orthogonal matrix, in a process called orthogonal transformation (Johnson & Wichern, 2007), that changes the initial loadings into factor loadings. These factor loadings have the same ability to reproduce the covariance matrix. The rotation continues until a simpler structure emerges, which can reveal if the factor loadings are interpretable. The underlying argument of any factor analysis is that if a group of variables are highly correlated, but have small correlations with variables in different groups, then each group of variables represents a single underlying construct (Johnson & Wichern, 2007). In Table 4.10, we summarize the factor loadings calculated through Varimax rotation.

Table 4.10: Estimated factor loadings of Migration Filter and R&D Filter indicators using Varimax Rotation

Indicator	Factor Loading Component 1	Factor Loading Component 2
Migration from outside Spain as a percentage (MOS)		0,88
Population born outside the region as a percentage (PBOR)	0,44	0,52
Population born outside Spain as a percentage (PBOS)		0,99
Foreigners with residency as a percentage (FR)		0,93
Locally mobile employees with more than 5 years of residency as a percentage (LME)	0,75	
Regionally mobile employees with more than 5 years of residency as a percentage (RME)	0,42	0,51
R&D investment per capita (RD)	0,97	
Spending on R&D personnel per capita (RDPER)	0,99	
Investments on full-time researchers per capita (RES)	0,98	
Tertiary education as a percentage (TEDU)	0,90	
Businesses with activities in innovation as a percentage (BI)	0,47	
Employment in high-tech sectors as a percentage (EMPHT)	0,61	
Importance of Components		
SS Loadings	6,13	3,69
Proportion of variance	0,41	0,25
Cumulative proportion	0,41	0,65
Cronbach's Alpha Test	0,79	0,79

Test of the hypothesis that 2 factors are sufficient. The chi square statistic is 438.5 on 76 degrees of freedom. The p-value is 2.17e-52

The Varimax rotation groups variables according to each factor. The indicators in the Migration Filter generally group along Factor Loading Component 2 and the indicators of the R&D Filter cluster with Factor Loading Component 1. The values are extremely high, in most cases greater than 0.7, strongly supporting the notion that the Migration Filter and the R&D Filter group along different factors. The Cronbach's alpha test reveals the internal consistency of a scale results; it equals 0.80 in the regression matrix, and 0,79 for each factor. Because a value greater than 0.7 is regarded as acceptable, we find strong support for scale consistency in our results (N. Schmitt, 1996).[22]

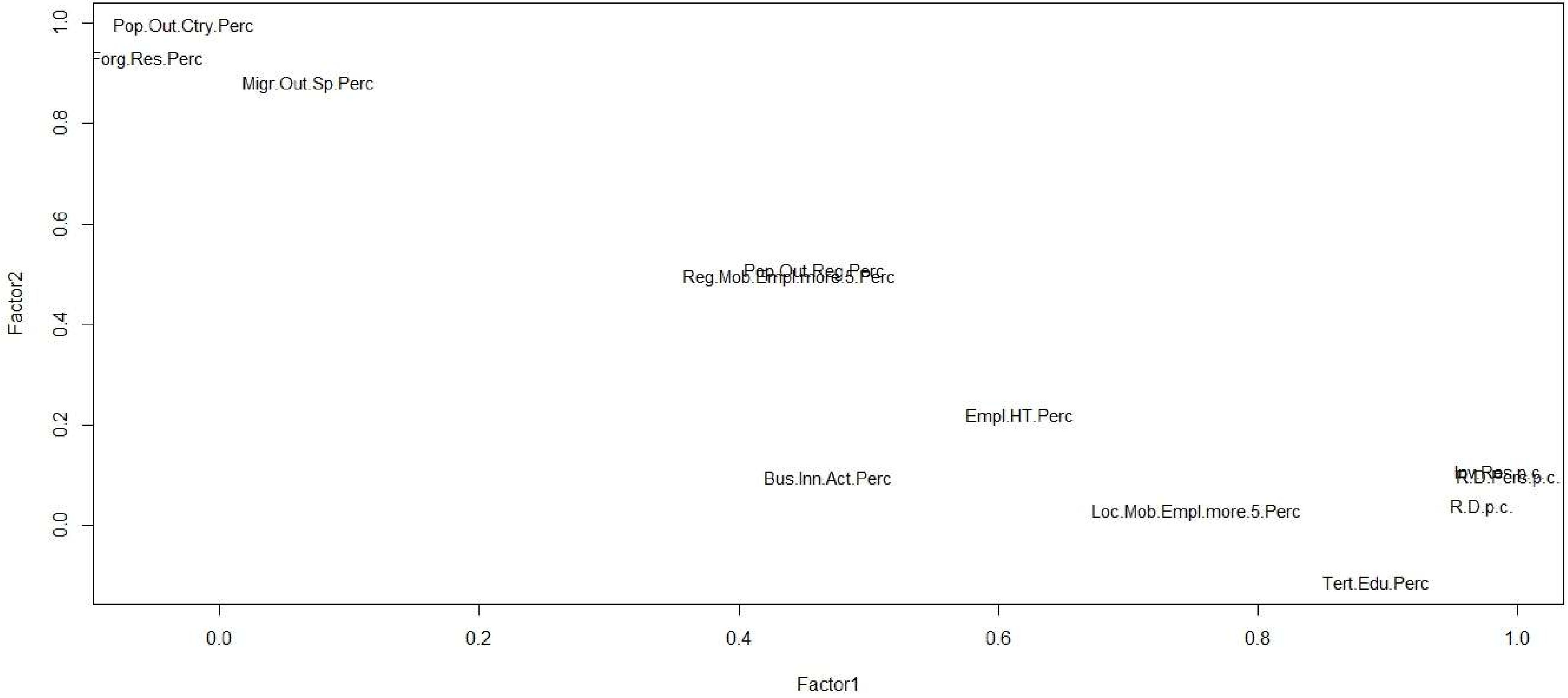
In line with our hypothesis, we might associate Factor Loading Component 2 with the tacit knowledge factor and Factor Loading Component 1 with the codified knowledge factor.

However, we also note three important exceptions. First, local mobile employees with more than five years' residency exhibit a value of 0.75 with the R&D Filter in Factor Loading Component 1. Second, the population born outside the region (0.46/0.51) and third regional mobility employees with more than five years' residency (0.44/0.50) both group approximately equally in both components.

Therefore, for local employees the Factor Loading Component 1 matters most (i.e. factors related to codified knowledge), whereas for international employees (immigrants), Factor Loading Component 2 matters most (i.e. factors related to tacit knowledge flows), as we show in Figure 4.5.

[22] The chi-square statistic is 438.5, with 76 degrees of freedom and a *p*-value of 2.17e-52. These findings indicate that two factors are sufficient to draw plausible conclusions.

Figure 4.5: Factor loadings and indicator positions



4.4.4.Regression Analysis

A regression function is needed to assess if two input categories, i.e. migration and R&D category is able to predict innovation output variables. To build the regression function, we proceed by calculating the individual scores obtained from factors 1 and 2. These calculated values of the dependent output variables then can be compared against real values. The regression analysis takes the following form:

$$Y_{i,t} = \alpha \quad + \beta_1 \text{ Factor Score } 1_t + \beta_2 \text{Factor Score } 2_t + \varepsilon,$$

where:

Y	**Innovation output of selected data between 2010 and 2012,**
i,t	**Innovation indicator i in year t (2010, 2011, 2012),**
▯	**Constant,**
Factor Score 1	**Score calculated for each region in time t of factor 1,**
Factor Score 2	**Score calculated for each region in time t of factor 2, and**
ε	**Error term.**

With these comparisons, we can leverage the Akaike information criterion (AIC), which balances the size of the residual sum of squares with the number of parameters in the model:

$r^2 = 1 - \frac{SS_{res}}{SS_{tot}}$	$\text{AIC} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$

The best possible model is the one with the smallest AIC values. We calculate each indicator of the output variable with both factors and with each factor alone. In addition, the obtained R-square value indicates how well the data fit a statistical model (ranging from 0 to 1), and the F-statistics measure the correlation between regions. We provide these measures, along with the constant $\boldsymbol{\alpha}$ and the values of each factor and the control variables, in Table 4.11. It contains 15 regressions. Each output variable (patents, not-patented inventions, industrial designs, trademarks, and business name applications) was calculated with both the Migration and R&D Filters, then with each filter alone. That is, each output variable was calculated according to three different regression functions. As this table shows, for patent applications (regressions 1–3) and non-patented inventions (regressions 4–6), both filters are highly significant and produce the lowest AIC. That is, both the Migration and the R&D Filter are significant for both patents and non-patented inventions.

Table 4.11: Regression equations with both factors and separate factors, with five output indicators as dependent variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
α	-1.298e-17	-1.865e-16	-3.958e-16	2.749e-16	4.354e-17	-1.865e-16	3.494e-16	2.369e-17	1.870e-16	-2.934e-16	-3.610e-16	-2.666e-16	-2.945e-16	-2.509e-16	-3.814e-17
Factor 1	**1.079e+00*****	6.043e-01**		**1.300e+00*****	6.674e-01**		4.579e-01	-4.334e-01		**-7.564e-02**	-2.605e-01		-7.224e-01*	-6.032e-01	
Factor2	**4.465e-01*****		6.565e-02	**5.955e-01*****		1.364e-01	8.384e-01***		**6.768e-01*****	**1.739e-01**		2.006e-01*	-1.121e-01		**1.429e-01**
GDP per capita	-1.718e-01	2.912e-01	8.205e-01***	-4.752e-01*	1.421e-01	7.206e-01***	-5.151e-01	3.542e-01	-9.399e-02	4.693e-01*	6.495e-01***	3.997e-01	7.001e-01	5.838e-01	3.572e-02
Population	-4.782e-02	4.085e-02	1.521e-01	1.334e-01	2.517e-01*	3.744e-01**	-9.129e-02	7.518e-02	-6.440e-03	9.016e-02	1.247e-01	7.614e-02	3.081e-01	2.858e-01	1.742e-01
Density	-4.026e-01**	-2.450e-01*	-3.231e-01*	-4.980e-01***	-2.879e-01*	-4.023e-01*	1.214e-01	4.172e-01*	1.551e-01	4.038e-01	4.651e-01	3.982e-01	4.908e-01	4.512e-01	4.376e-01**
Dependent variable															
Patents	X	X	X												
Not-patented inventions				X	X	X									
Industrial designs							X	X	X						
Trademarks										X	X	X			
Business names													X	X	X
Statistical Results															
AIC	**104.46**	106.78	147.89	**110.73**	114.63	146.83	114.13	149.56	**112.46**	**112.23**	134.51	132.87	141.72	148.86	**140.74**
R^2	0.71	0.62	0.53	0.72	0.56	0.46	0.57	0.24	0.53	0.68	0.66	0.67	0.48	0.48	0.40
F	22,05 on 5 and 45 DF	18.5 on 4 and 46 DF	12.91 on 4 and 46 DF	23.7 on 5 and 45 DF	14.55 on 4 and 46 DF	9.859 on 4 and 46 DF	11.8 on 5 and 45 DF	3.588 on 4 and 46 DF	13.21 on 4 and 46 DF	18.71 on 5 and 45 DF	22.43 on 4 and 46 DF	23.81 on 4 and 46 DF	8.398 on 5 and 45 DF	10.48 on 4 and 46 DF	7.714 on 4 and 46 DF
Number Ob.	51	51	51	51	51	51	51	51	51	51	51	51	51	51	51

Figure 4.6: Patents per capita, real vs. predicted values, Factors 1 and 2

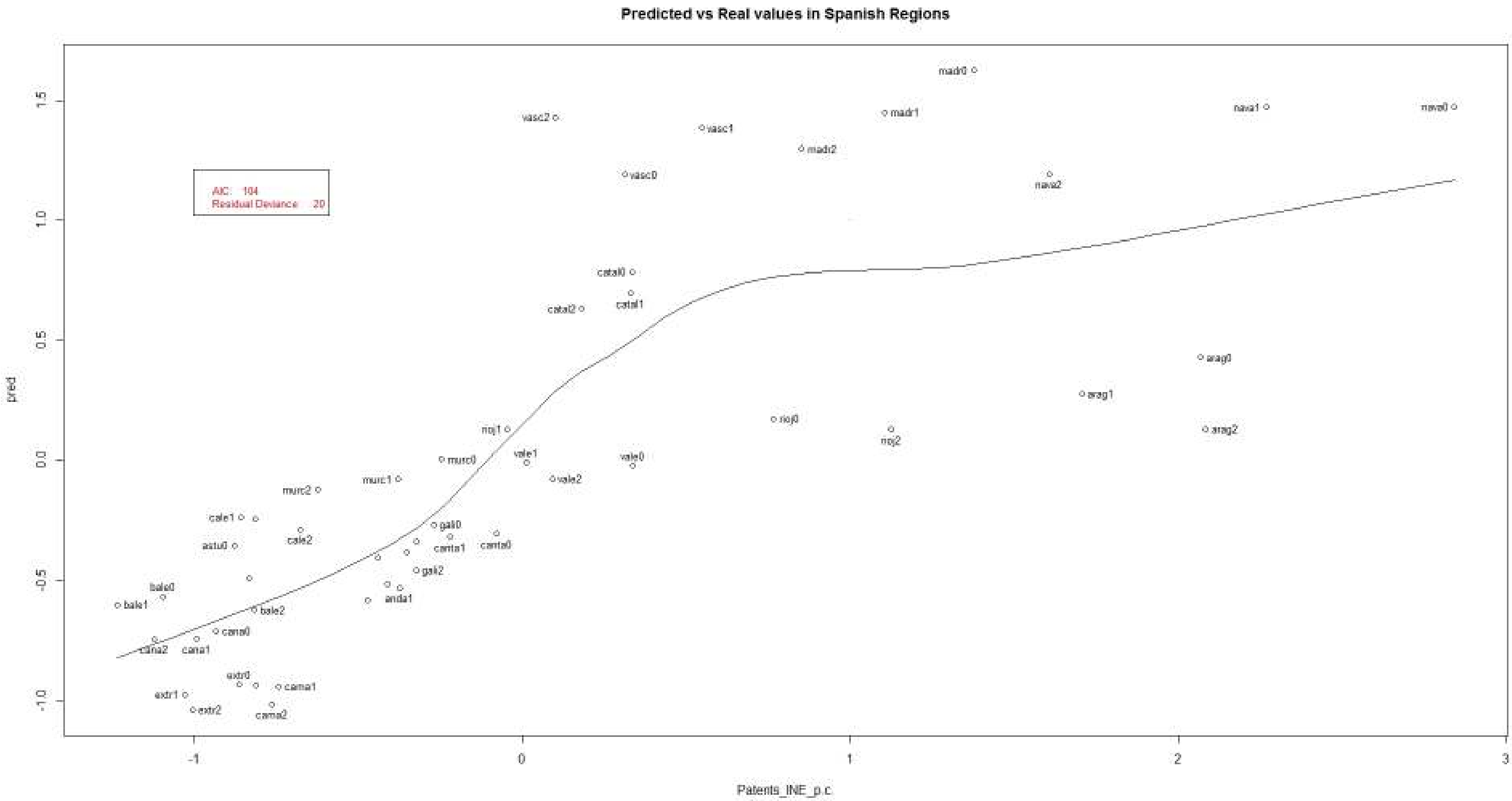


Figure 4.7: Not-patented inventions, real vs. predicted values, Factors 1 and 2

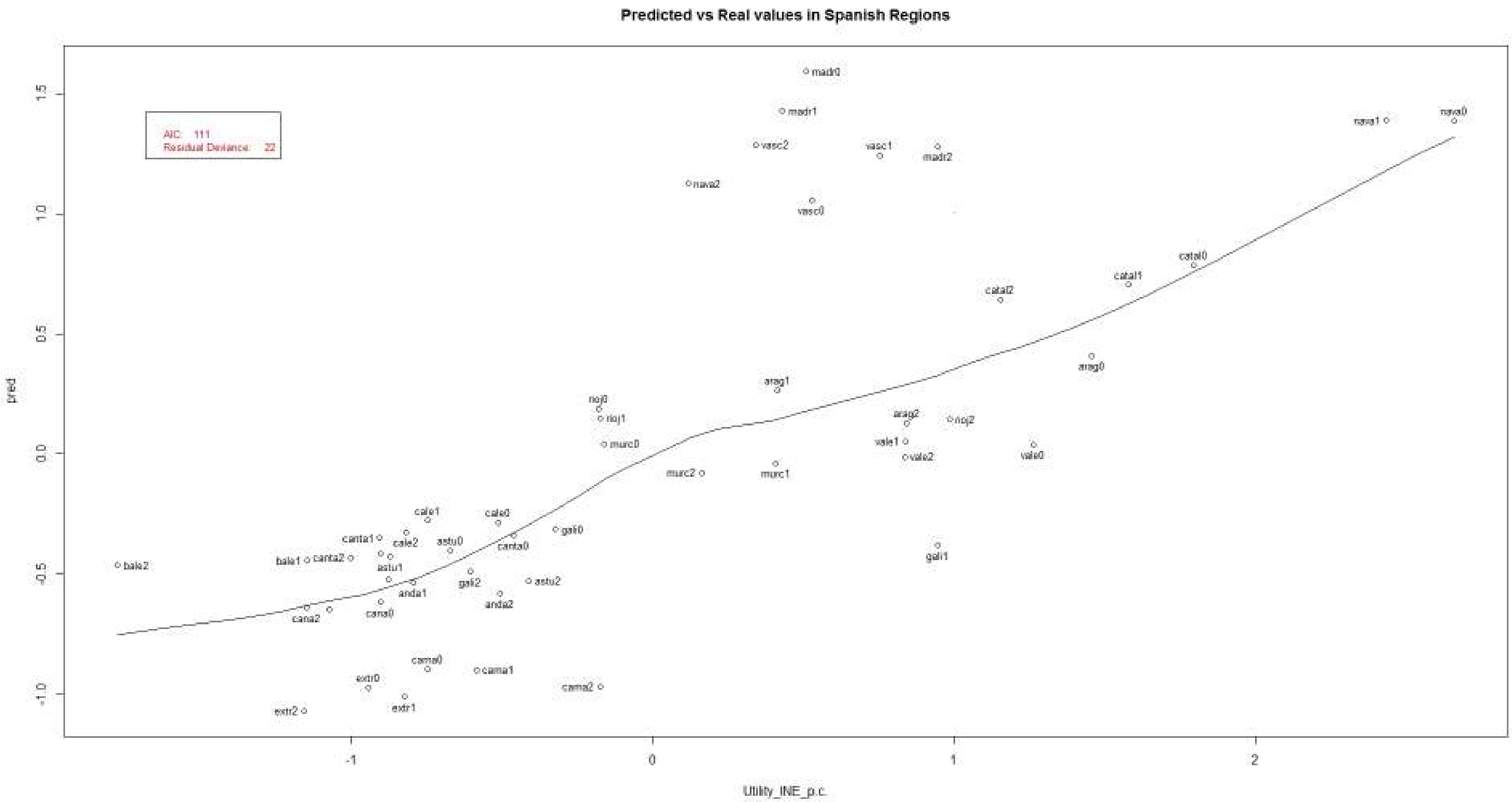
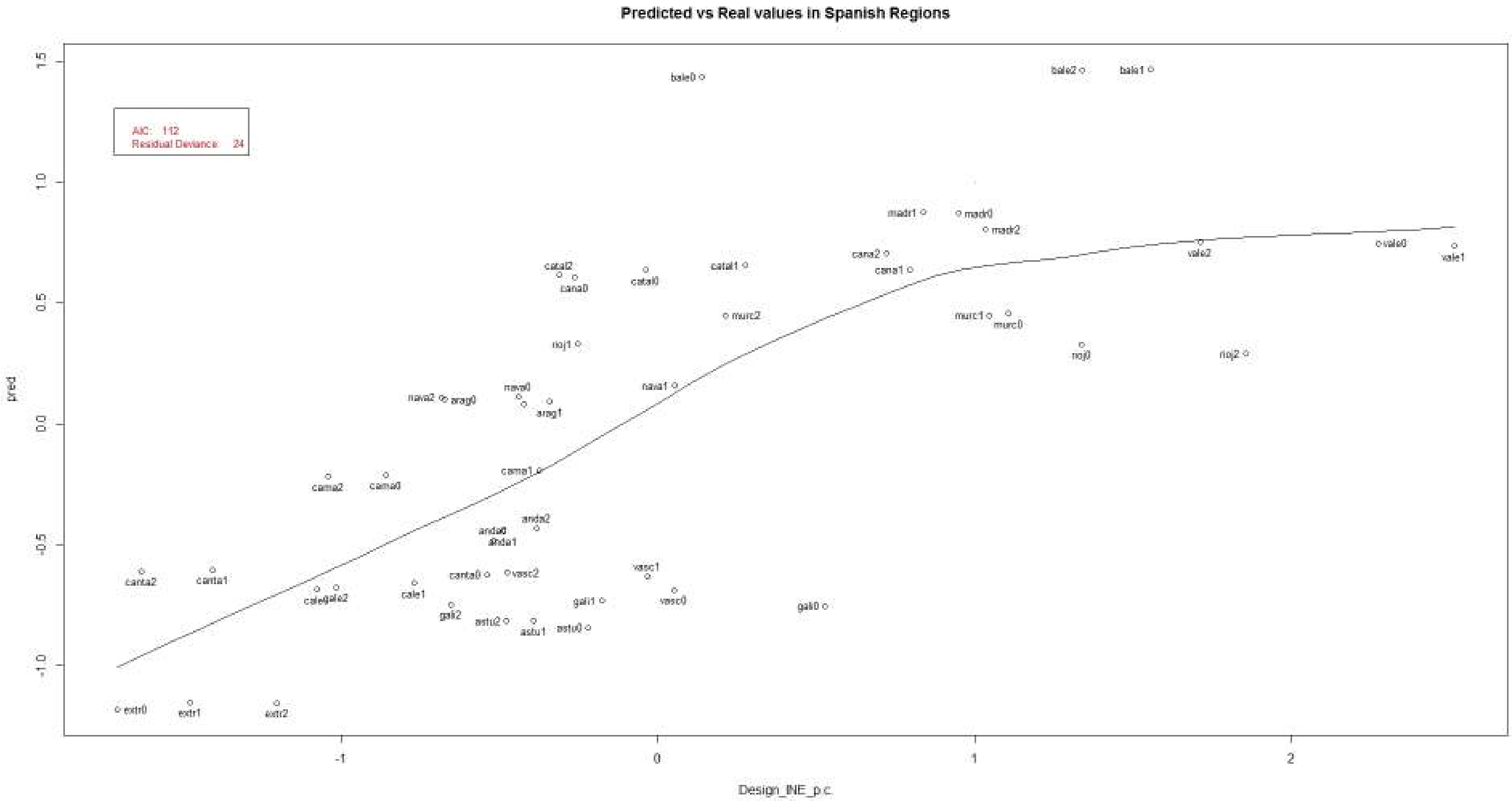


Figure 4.8: Industrial design applications, real vs. predicted values, Factor 2



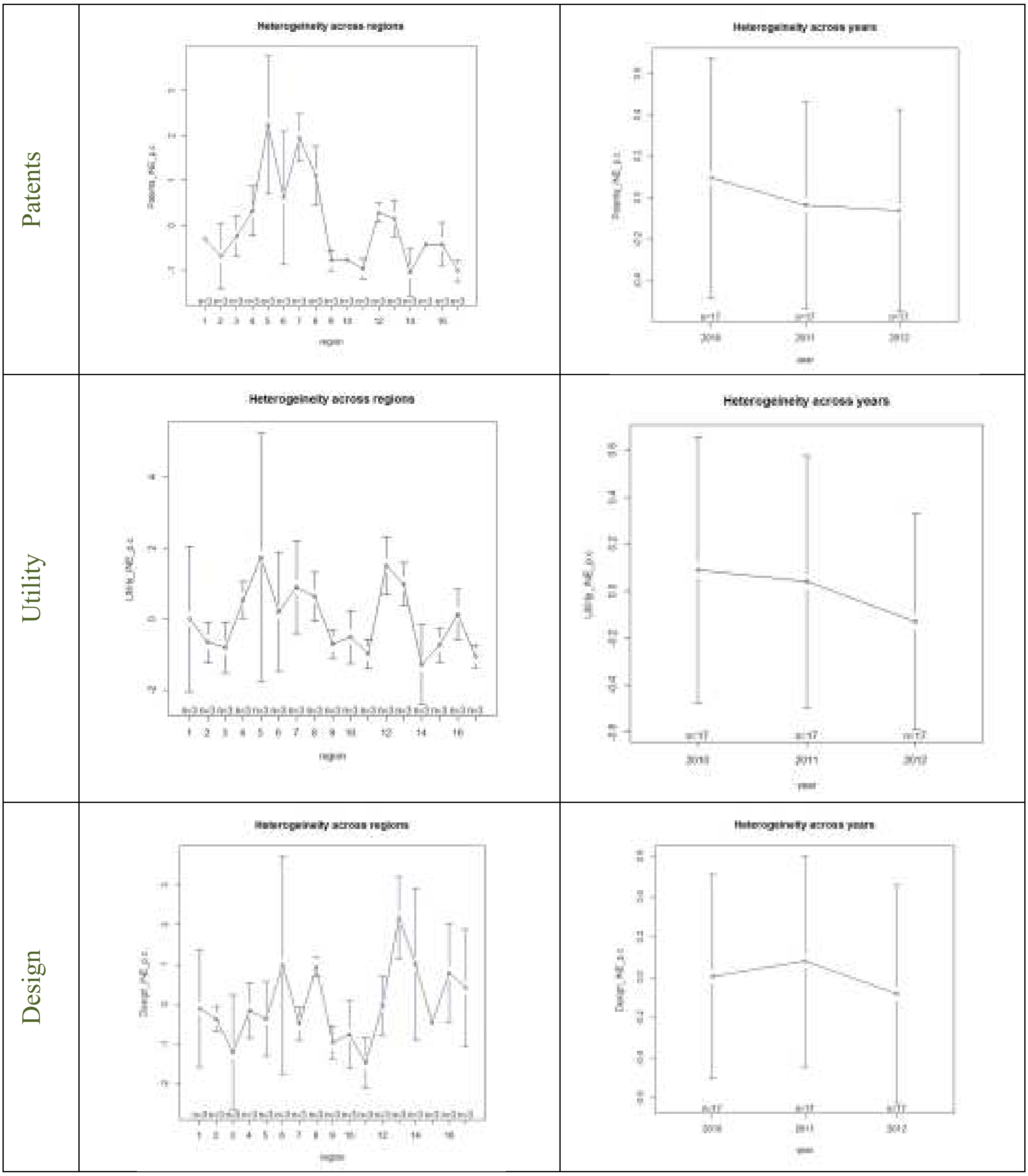
For the industrial design applications dependent variable (regressions 7–9), the best possible model, with the lowest AIC, was regression 9 with only the Migration Filter, as a positive, highly significant independent variable. For trademark applications (regressions 10–12) and business name registrations (regressions 13–15), we observe no regressions with significant independent variables. Figure 4.6, 4.7, and 4.8 compare the estimated values of the regressions with the real values for the output variables for which we can confirm the model: patents and non-patented inventions with both filters and AICs of 104.46 and 110.73, respectively, and industrial designs with only the Migration Filter and an AIC of 112.46.

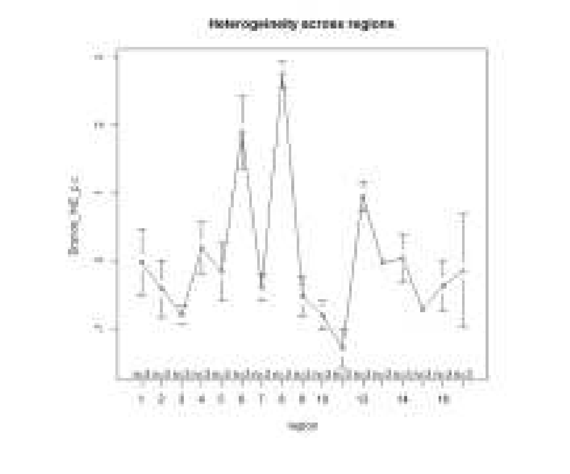
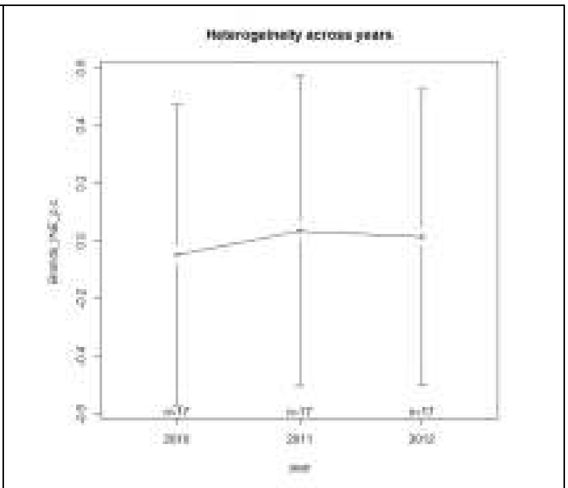
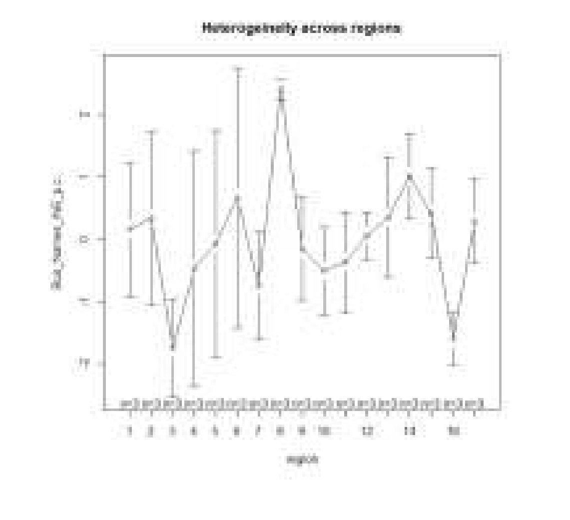
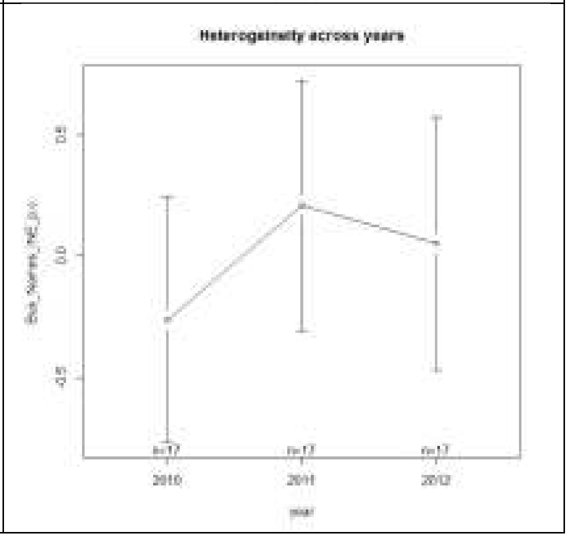
4.4.5. Fixed Effects and Random Effects Model

Panel data has some drawbacks when it is analyzed through ordinary least squares (OLS). For instance, the repeated observations in each region makes them dependent, although they do allow us to get better estimates (Greene, 2003). These fixed effects caused by cross-region dependency or correlations between countries can be sorted by means of the fixed effects model or the random effects model. The Hausmann test is applied to check which one of these methodologies should be applied.

The fixed effects model takes into account that each region has a fixed effect that shifts the regression line up or down. In contrast, the random effects model treats each independent variable as if they arise from random causes. The figures in 4.9 below shows the heterogeneity of the dependent variables with respect to the region and the year.

Figures 4.9: Heterogeneity of the dependent variables with respect to region and year



Brands		
Business Names		

Figures 4.9 above shows that depending on the dependent variables, heterogeneity increases or decreases. For instance, we can see that there seems to be a larger heterogeneity in Business Names applications than Design applications. The Fixed effects and the random effects takes into account this heterogeneity and provides information on the validity on the 2 factors selected to explain the 5 dependent variables Patent applications, Non-Patented Inventions (Utility), Design applications, Brands registrations and Busienss Names registrations. Below the formula of the fixed effects model:

Formula 3.2: Fixed Effects Model:

$$Y_{it} = \beta_1 Factor\ 1_{it} + \beta_1 Factor\ 2_{it} + \alpha_i + u_{it}$$

where

– αi (i=1….n) is the unknown intercept for each entity (n entity-specific intercepts).
– Yit is the dependent variable where i = entity and t = time.
– β1 is the coefficient for that IV,
– uit is the error term

The fixed effects model analyses the dependent variable over time within the region (Torres-Reyna, 2007). Each region has its own individual characteristic when influencing the dependent variable and the fixed effect model controls for this unique effect, which is valid to the region alone. Therefore, it removes the effect of time-invariant characteristic and allows determining the net effect of the 2 Factors on the dependent variable. However, if the error terms are correlated, then the fixed affects model is not suitable and the relationship needs to be explained by the random effects model (Torres-Reyna, 2007). The fixed effects model on the 5 dependent variables provides us with the following results:

Table 4.12.: Results of the Fixed Effects Model with Factor 1 and Factor 2 as Independent Variables and 5 Dependent Variables:

Patent Applications Balanced Panel: N=17, t=3, N=51	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**
Factor 1	1.22096	0.55236	2.2104	**0.03512 ***
Factor 2	-1.43483	1.37296	-1.0451	0.30463
GDP P.C. (Control Variable)	-0.41211	0.96938	-0.4251	0.67388
Population (Control Variable)	2.91179	4.16152	0.6997	0.48969
Population Density (Control Variable)	-6.80737	6.42044	-1.0603	0.29778
Total Sum of Squares: 2,3449				
Residual Sum of Squares: 1,7739				
R-Squared: 0,2434				
Adj. R-Squared : 0,1384				
F-statistic: 1.86674 on 5 and 29 DF, p-value: 0.13109				
Non-Patented Applications (Utility) Balanced Panel: N=17, t=3, N=51	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**

Factor 1	2.6972	1.0837	2.4890	**0.0188 ***
Factor 2	-2.5669	2.6936	-0.9530	0.3485
GDP P.C. (Control Variable)	-2.4341	1.9018	-1.2799	0.2107
Population (Control Variable)	3.3954	8.1643	0.4159	0.6806
Population Density (Control Variable)	-7.8821	12.5960	-0.6258	0.5364
Total Sum of Squares: 8,5844				
Residual Sum of Squares: 6,8276				
R-Squared: 0,20465				
Adj. R-Squared : 0,11637				
F-statistic: 1.49241 on 5 and 29 DF, p-value: 0.22283				
Design Applications Balanced Panel: N=17, t=3, N=51	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**
Factor 1	0.24416	1.12013	0.2180	0.8290
Factor 2	1.02242	2.78423	0.3672	0.7161
GDP P.C. (Control Variable)	0.95132	1.96580	0.4839	0.6321
Population (Control Variable)	-4.47435	8.43913	-0.5302	0.6000
Population Density (Control Variable)	8.63155	13.02001	0.6629	0.5126
Total Sum of Squares: 7,6335				
Residual Sum of Squares: 7,295				
R-Squared: 0,04434				
Adj. R-Squared : 0,02521				
F-statistic: 0.269101 on 5 and 29 DF, p-value: 0.9263				
Brands Registrations Balanced Panel: N=17, t=3, N=51	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**
Factor 1	-0.018375	0.306709	-0.0599	0.95264
Factor 2	2.298938	0.762364	3.0155	**0.00529 ****
GDP P.C. (Control Variable)	-0.524046	0.538267	-0.9736	0.33832
Population (Control Variable)	-1.805671	2.310766	-0.7814	0.44089
Population Density (Control Variable)	-0.770612	3.565081	-0.2162	0.83038
Total Sum of Squares: 0,77038				
Residual Sum of Squares: 0,54694				
R-Squared: 0,29003				

Adj. R-Squared : 0,16492				
F-statistic: 2.3694 on 5 and 29 DF, p-value: 0.064102				
Business Names Applications Balanced Panel: N=17, t=3, N=51	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**
Factor 1	-2.78214	0.88237	-3.1530	**0.00374 ****
Factor 2	0.15975	2.19324	0.0728	0.94244
GDP P.C. (Control Variable)	2.70529	1.54854	1.7470	0.09122 .
Population (Control Variable)	6.61508	6.64784	0.9951	0.32793
Population Density (Control Variable)	-14.95446	10.25638	-1.4581	0.15557
Total Sum of Squares: 6,5048				
Residual Sum of Squares: 4,5268				
R-Squared: 0,30408				
Adj. R-Squared : 0,17291				
F-statistic: 2.53428 on 5 and 29 DF, p-value: 0.050787				

Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

The fixed effects model shows that the large majority of the factors are not significant, meaning that according to this model, no significant influence is expected from the factors on the dependent variable.

Exceptions to this rule are Factor 1 on dependent variable Patent applications, Factor 1 on Non-Patented applications, Factor 2 on Brands registrations, as well as Factor 1 on Business Names applications. Regarding the latter, this factor 1 has a negative influence on Busienss Names applications.

Subsequently, we confirm the model to be applied by first analyzing the panel data with the random effects model. The random effects model is calculated by the following formula:

Formula 3.2: Random Effects Model:

$$Y_{it} = \beta \;\; Factor\ 1_{it} + \beta \;\; Factor\ 2_{it} + \alpha_i + u_{it} + {}^{\varepsilon}{}_{it}$$

where
– αi (i=1….n) is the unknown intercept for each entity (n entity-specific intercepts).
– Yit is the dependent variable where i = entity and t = time.
– β1 is the coefficient for that IV,
– uit is the error term

The Random effects model assumes that the error term is not correlated with the predictors. This allows time-invariant variables play a role as independent variables (Torres-Reyna, 2007). The following table 4.13 shows the calculated values for the random effects model:

Table 4.13.: Results of the Random Effects Model with Factor 1 and Factor 2 as Independent Variables and 5 Dependent Variables:

Patent Applications Balanced Panel: N=17, t=3, N=51	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**
Intercept	4.5621e-17	1.4563e-01	0.0000	1.00000
Factor 1	1.0334e+00	2.9385e-01	3.5169	0.00101 **
Factor 2	4.5017e-01	2.0229e-01	2.2254	0.03111 *
GDP P.C. (Control Variable)	-1.4400e-01	3.2663e-01	-0.4409	0.66143
Population (Control Variable)	-3.7808e-02	1.7938e-01	-0.2108	0.83401
Population Density (Control Variable)	-3.9683e-01	2.0699e-01	-1.9172	0.06157 .
Total Sum of Squares: 4,899				
Residual Sum of Squares: 2,6088				
R-Squared: 0,46748				
Adj. R-Squared : 0,41248				
F-statistic: 7.90085 on 5 and 45 DF, p-value: 2.0802e-05				
Non-Patented Applications (Utility) Balanced Panel: N=17, t=3, N=51	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**
Intercept	2.9449e-16	1.0299e-01	0.0000	1.0000000
Factor 1	1.3393e+00	2.5854e-01	5.1804	5.034e-06 ***
Factor 2	6.6573e-01	1.5775e-01	4.2202	0.0001168 ***

GDP P.C. (Control Variable)	-5.3560e-01	2.7106e-01	-1.9759	0.0543111 .
Population (Control Variable)	1.2449e-01	1.3018e-01	0.9563	0.3440075
Population Density (Control Variable)	-5.0686e-01	1.4851e-01	-3.4131	0.0013689 **
Total Sum of Squares: 25,729				
Residual Sum of Squares: 10,076				
R-Squared: 0,60836				
Adj. R-Squared : 0,5368				
F-statistic: 13.9805 on 5 and 45 DF, p-value: 2.9761e-08				
Design Applications Balanced Panel: N=17, t=3, N=51	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**
Intercept	3.1697e-16	1.5112e-01	0.0000	1.0000000
Factor 1	4.3713e-01	3.6336e-01	1.2030	0.2352589
Factor 2	8.5939e-01	2.2668e-01	3.7913	0.0004436 ***
GDP P.C. (Control Variable)	-5.0832e-01	3.8500e-01	-1.3203	0.1934024
Population (Control Variable)	-8.9561e-02	1.8991e-01	-0.4716	0.6394917
Population Density (Control Variable)	1.0668e-01	2.1728e-01	0.4910	0.6258198
Total Sum of Squares: 15,989				
Residual Sum of Squares: 10,336				
R-Squared: 0,35355				
Adj. R-Squared : 0,31196				
F-statistic: 4.92217 on 5 and 45 DF, p-value: 0.0011197				
Brands Registrations Balanced Panel: N=17, t=3, N=51	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**
Intercept	-1.3537e-16	1.7577e-01	0.0000	1.00000
Factor 1	1.9438e-01	2.3979e-01	0.8106	0.42184
Factor 2	4.1539e-01	2.1375e-01	1.9433	0.05825 .
GDP P.C. (Control Variable)	8.4179e-02	3.0324e-01	0.2776	0.78260
Population (Control Variable)	2.8516e-04	2.0978e-01	0.0014	0.99892
Population Density (Control Variable)	3.8438e-01	2.4272e-01	1.5836	0.12028
Total Sum of Squares: 1,4309				
Residual Sum of Squares: 0,95139				
R-Squared: 0,33513				

Adj. R-Squared : 0,2957				
F-statistic: 4.5365 on 5 and 45 DF, p-value: 0.0019628				
Business Names Applications Balanced Panel: N=17, t=3, N=51	**Estimate**	**Standard Error**	**t-value**	**Pr(>|t|)**
Intercept	-4.5717e-16	1.9247e-01	0.0000	1.000000
Factor 1	-1.1802e+00	4.2139e-01	-2.8007	0.007489 **
Factor 2	-3.1891e-01	2.7665e-01	-1.1527	0.255102
GDP P.C. (Control Variable)	1.1423e+00	4.5763e-01	2.4962	0.016283 *
Population (Control Variable)	3.9983e-01	2.3914e-01	1.6720	0.101474
Population Density (Control Variable)	5.1593e-01	2.7503e-01	1.8759	0.067164 .
Total Sum of Squares: 10,216				
Residual Sum of Squares: 7,2548				
R-Squared: 0,28989				
Adj. R-Squared : 0,25578				
F-statistic: 3.67402 on 5 and 45 DF, p-value: 0.0071436				

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The Random effects model provides us with very different results as to the significance of the factors and consequently, its significance in influencing the dependent variables. Both factors are positive and highly significant for Patent applications and Non-Patented inventions. With regards to Design applications, only Factor 2 is highly significant and positive, no significant factor can be observed for Brands applications and with dependent variable Business Names applications, only Factor 1 is highly significant but negative. Therefore, depending on the model applied the interpretation will differ substantially. The Hausman-test will tell us which model should be used for which dependent variable Y. The next table displays the results obtained:

Table 4.14.: Hausman-Test to Determine the model to use: Fixed or Random Effects

Patent Applications	Non-Patented Applications (Utility)	Design Applications	Brands Registrations	Business Names Applications

Chisq = 2.6453, df = 5, p-value = 0.7545	chisq = 2.7955, df = 5, p-value = 0.73	chisq = 1.0885, df = 5, p-value = 0.96	chisq = 10.8767, df = 5, p-value = 0.05	chisq = 6.5269, df = 5, p-value = 0.25
Alternative hypothesis: one model is inconsistent	alternative hypothesis: one model is inconsistent	alternative hypothesis: one model is inconsistent	alternative hypothesis: one model is inconsistent	alternative hypothesis: one model is inconsistent
Random Effects should be used	**Random Effects should be used**	**Random Effects should be used**	**Fixed Effects should be used**	**Random Effects should be used**

The Hausman-test suggest to use Random effects model if the p-value of the test is above 0,05. As can be observed in the table 4.14 it is suggested to use for all dependent variables except for Brands registrations the Random effects model. The Fixed effects model should be used for Brands registration.

This leads us to the following results as to the significance of the Factors and control variables. With regard to Patent applications, both factors are positive and highly significant in influencing the dependent variable. The control variables are not significant. The same can be said for Non-Patented Inventions. Here, control variable Population Density is also highly significant together with Factor 1 and Factor 2.

With regards to Design Applications, only Factor 2 is highly significant and positive. Factor 1 and all control variables are not significant. The Fixed effects model should be used for dependent variable Brands registrations. Here, table 4.12 shows that only Factor 1 is highly significant. Last but not least, Factor 1 is highly significant in the case of Business Names applications together with control variable GDP per capita. It is important to stress that Factor 1 shows a negative value.

4.4.6.Discussion of Results

Analyzing the correlations between the input and the output variables it could be observed that many codified knowledge variables such as R&D investment, R&D personnel and tertiary education were highly correlated to patent applications. This result was as expected, as in line with previous studies such as Kline (1985).

What could also be seen here is that immigrants contribute to patent applications as well. This could be via skills and by adding their codified and tacit knowledge. Nevertheless, it could also be observed that for some indicators, notably Design applications, it is only the variable migration via Factor 2 that was highly correlated to this output indicator and highly significant in influencing the dependent variable. An observation that could be confirmed by means of the PCA through the Varimax rotation.

Immigration, especially from outside the locality contribute with a component that is orthogonal to the codified knowledge component. We assume that this is the tacit knowledge component, since it grows in relevance the more heterogeneous the migrants. While local mobility contribute only by adding their skills, regional migrants contribute with both, while migrants from outside Spain contribute with tacit knowledge only. Although it does not add codified knowledge, this contribution is positive and significant as it has been confirmed by means of the regression analysis.

The PCA regression analysis confirms that the migration component adding tacit knowledge into the region, and the R&D component adding codified knowledge contribute independently towards higher patent activity and non-patented inventions. In the case of industrial designs, only the migration component is positive and significant. On the other hand, the hypothesis could not be confirmed for trademark applications and business names applications. Predictors were positive but not statistically significant.

The Fixed effects and the random effects model have showed that both factors are highly significant and positive in explaining Patent Applications and Non-Patented Inventions. With regards to Design applications, only Factor 2, that is the migration component, has proved to be highly significant. The opposite occurs with Brands registration, where only Factor 1 is positive and highly significant. With regards to Business Names applications, it is the control variable GDP per capita and Factor 1 that are highly significant, although the latter with a negative sign.

When we analyze the autonomous communities in Spain for patent applications (Figure 4.6), we find that in Extremadura, Galicia, Cantabria, Valencia, Catalonia, Madrid, and Navarra, the regression equation results are very similar to the real values. In Aragon, the real values are higher than the calculated ones, insofar as for the Basque Country, the predicted values are higher. Navarra's patent activity is fairly well predicted on the highest level in Spain while the rest of the regions are on a very low patent activity.

With regard to non-patented inventions (Figure 4.7), nearly all regions (except Madrid and the Basque Country, which showed lower real values) produced real values that were very similar to our calculated values. Extremadura and Canary Islands have higher than predicted activity in Not-patented inventions albeit at a very low level. The rest of the regions are very well predicted with Navarra at the highest level, followed by Cataluña, Aragón, Valencia, Murcia and La Rioja.

We recall that in the case of PCA regression analysis with design applications as dependent variable only the migration component is significant and used as predictor (Figure 4.8). We identify the Balearic Islands as a clear outlier, with lower than expected values of innovation output. This result could reflect its singularity, in that this region strongly depends on tourism. On the other hand the predicted values in the Basque Country, Galicia, and Asturias also are lower than the real values as they are below the line that shows the average for all the regions in Spain. The rest are fairly well predicted with Valencia at highest level followed by La Rioja, Murcia, Madrid, Canary Islands and Catalonia. Navarra and Aragón.

4.5. Conclusion

This analysis reveals some notable conclusions. First, we confirm our hypothesis that a heterogeneous tacit knowledge base, as a result of immigration, increases the innovation outcomes for local and regional production systems in most cases. Specifically, for patents, non-patented inventions, and industrial designs outputs, a heterogeneous tacit knowledge base seems essential. Both migrations and R&D investments contribute, along different factors. For patenting and non-patented inventions, the migration component is complementary to the R&D component, but in the case of industrial designs, only migrations appear necessary. However, we did not confirm our hypothesis for outcomes such as trademark and business name applications.

Second, we observe that larger geographic scope for migrations prompts a greater alignment with the tacit knowledge component. That is, local mobile migrant employees with more than five years' of residency constitute a variable that groups together with codified knowledge indicators, whereas immigrant workers from outside Spain match with the tacit knowledge component. Regional mobile employees with more than five years' residency align approximately equally with both codified and tacit knowledge components. We interpret it in the following way: the more local the mobility is, the lower the cognitive distance among these individuals, thus the tacit knowledge component makes a lower contribution to innovation.

In contrast, the impact of immigrant workers from further away is more strongly associated to the tacit knowledge component. This component contributes to innovation by different means than R&D or formal education. This component is clearly positive and significant, and relates to transfers of tacit knowledge that are bridged from enfolded communities into the social capital of the region and from tacit knowledge related to the individual skills of the migrants.

Regional migrants contribute in equal terms with codified and tacit knowledge whereas local migrants do not contribute to innovations other than along the codified knowledge component. Therefore, since immigration from outside Spain contributes more to a heterogeneous tacit knowledge base than local migrants, our hypothesis based on the innovation paradox and the distinction of codified and tacit knowledge can be confirmed. While investment in R&D and other codified knowledge indicators contributes towards cognitive proximity of codified knowledge bases, immigration makes tacit knowledge more heterogeneous and contributes towards cognitive distance of tacit knowledge bases available in the region.

These findings recommend developing an R&D policy simultaneously with a strategy to build a heterogeneous tacit knowledge base to increase innovation output in RIS. Migrations contribute positively and significantly to increasing patents, non-patented inventions, and industrial designs. That is, heterogeneous tacit knowledge is critically important for innovations that rely on tacit knowledge. Codified knowledge investments, in the form of R&D, cannot replace tacit knowledge. These knowledge types are complementary and need to be developed together. The identified outliers in the autonomous communities show imbalances of codified and tacit knowledge, suggesting their poor innovation efficiency, because the regression analysis has identified the migration and R&D category as positive and significant components.

Autonomous communities with large stocks of codified knowledge and homogenous tacit knowledge should concentrate on developing the latter before considering more investment in R&D (and vice versa). The Basque Country represents an excellent candidate for the further development of a heterogeneous tacit knowledge base; La Rioja, Valencia, and the Balearic Islands instead could substantially improve their innovation outputs by focusing on codified knowledge stock investments.

Considering that recent Eurobarometer data indicate that immigration is ranked as the most important concern in EU public opinion (Commision, 2015), any debate should integrate information about these benefits of migration for economic development, to balance the current focus on costs. Our analysis suggests that increasing migration flows, not just within Spain but also across EU regions, may leverage the important benefits that can result from rich heterogeneous tacit knowledge bases.

Fourth, our study helps extend the understanding of the proximity paradox. By differentiating codified knowledge from tacit knowledge, we propose a differentiated strategy for collaborative innovation activities, depending on the knowledge type involved. Specifically, actors in a RIS should work to decrease the cognitive distance of codified knowledge, but should increase the cognitive distance of tacit knowledge. In this sense, our work contributes to both tacit knowledge literature (Haruyama, 2009; Michael Polanyi, 1966) and RIS literature (Bathelt, et al., 2004; Cooke, 2001; Gertler, 2003; Lundvall, et al., 2002).

We also hope that continued research tackles some of the main limitations of this study. The focal relationships should be analyzed in the RIS of the EU, once adequate indicators become available. We consider migration as a variable to indicate a heterogeneous tacit knowledge base, but multiple other indicators also could contribute to form a heterogeneous tacit knowledge base, such as varied industries, sectors, the inclusiveness of the labor market, bilingual territories, inward foreign direct investment, or foreign ownership of domestic inventions. Case studies could determine if transfers or physical proximity of co-workers across different departments improves innovativeness in real-world settings. Multiple experiments, involving innovation collaboration among departments in the same firm or among firms at local levels (to exchange tacit knowledge) or extra-regional levels (to exchange codified knowledge) could also be designed and implemented.

Finally, we had a limited number of observations, due to the difficulty of obtaining available migration data sets. Statistical offices increasingly provide these data not only for Spain but throughout Europe. With this study, we demonstrate that codified and tacit knowledge are input variables with complementary contributions, using a PCA that includes both components as input variables in a regression analysis. The design of the study chould be applied in further studies to investigate different territories throughout the world.

CHAPTER 5

CONCLUSIONS AND MAIN RESEARCH AND POLICY IMPLICATIONS

5. Conclusions and Main Research and Policy Implications

5.1. Main Findings

The three chapters together provide a comprehensive analysis on the role of openness in creativity and innovation. Openness is considered as a fundamental ingredient to integrate the tacit knowledge that complements the codified knowledge stock. This study distinguishes internationalisation from openness, in that the former is the exchange of codified knowledge based upon international collaborations, whilst the second is tacit knowledge inflows based upon openness to global sources of human and social capital. The first chapter analysed nations, while the last two chapters analysed regions.

One of the main findings refers to international R&D&I collaborative activities. Even though such collaboration is beneficial to the nations and regions that have already acquired a large stock, and have further upgraded their stock of codified knowledge, it is still less relevant than openness that brings tacit knowledge into the nations and regions. Nations and regions that upgrade their stock of codified knowledge, improve their absorptive capacity, which enables them to benefit from further codified knowledge transfer. Openness enables inflow of tacit knowledge, which makes the tacit knowledge stock more heterogeneous in these regions.

The first chapter concluded that openness of a nation has proved to be more significant than internationalisation in terms of correlations. This finding is of particular relevance for policy-makers, since most R&D&I policies target internationalisation activities rather than policies to improve openness. Internationalisation policies are useful for countries that have already acquired sufficient absorptive capacity, and are especially useful for collaboration within the private sector.

Moreover, innovations that are closer to the market seem to get more benefit from internationalisation activities. Therefore, benefits from the international transfer of codified knowledge through collaborations are limited to specific cases. An example would be collaborations between an automotive plant and a sector firm from another region or country. The technology in the field of gasoline engines is very mature and close to the market, therefore collaborations with other plants would make sense to develop a new technology and find synergies by means of complementary knowledge bases.

Openness seems to have a more widespread impact in that, non-native personnel in the territory and foreign-born human resources in science and technology are essential for exploitation and exploration activities and outputs. The latter being innovations that are generally more radical, i.e. new technology (Greve, 2007). It was also observed that countries which show lower than average values of non-native population were underperformers in the codified knowledge innovation input versus innovation output ratio, suggesting that higher values of non-native population generate higher innovation output.

Regarding research on openness and its influence on the creative workforce within European regions, there seems to be confirmation that greater openness leads to higher creativity (i.e. bigger creative workforce). Statistical analysis confirmed that the codified knowledge factor and the tacit knowledge factor are the two principal components which act in a complementary manner but are not interchangeable. The first principal component is the codified knowledge component and the second principal component is the tacit knowledge component. The first and the second component have a positive impact on creative workforce numbers in the regions of Europe. The two principal components are defined as being orthogonal to each other and therefore each component has a direct positive impact and is not replaceable.

Nevertheless, analysing the openness variable in detail, it is observed that not all indicators align along the same principal component that represents tacit knowledge. Female participation in the labour market aligns along the same component as migrations and youth participation aligns with labour market indicators. Nevertheless, female participation contributes negatively to creative industries. This means that women in the labour market do not contribute towards creative workforce. This surprising result need to be investigated further.

Creativity and innovation are two closely related concepts that measure the ability of the economy to create new goods, services, processes, common practices, etc. Creativity is regarded to be truly novel but innovation can consist of already existing ideas transferred into a new setting. Therefore, the role of openness on both radical ideas, i.e. creativity and innovations was tested.

The study also investigated lags between the predictors of codified and tacit knowledge and the dependent variable creative workforce. No evidence for time lags was found. The principal component regression analysis was performed using input and output data from the same year, because the impact of input indicators materialises in the same year into output.

The results from the regression analysis indicate that migrations as well as youth participation in the labour market have a complementary role to codified knowledge stock, for building creative workforce numbers in European regions. In particular, the migrations indicator shows a very high influence on building the principal component, i.e. it is by far the most important indicator for increasing the creative workforce in the labour market. Taking into account these results, the subsequent chapter analysed a number of migration indicators and their influence on innovations.

The complementary chapter three tests the role of migrations as an openness component on innovations. The research was conducted in Spanish regions on 5 innovation indicators that permitted the drawing up of the 5 principal component regression equations. This hypothesis builds on the ones proposed by Hunt (2009), Niebuhr (2010) and Saxenian (Saxenian, 2002b), who opined that immigration is beneficial for the recipient society because it fosters patent registrations and boosts entrepreneurship. Moreover, this argument follows Parrilli's (Parrilli, 2012) approach to any form of community migrations (not only the one focused on high-skilled people) may benefit the recipient society in the form of new values and good practices introduced in the region.

These are the so-called heterogeneous tacit knowledge bases that complement the increasing codified knowledge stock.

The findings in this paper confirm the hypothesis in three of the five regression equations. Openness has a positive impact on patents, non-patented inventions and industrial designs. Therefore, a heterogeneous tacit knowledge base in the form of migrations leads to higher registrations of patents, non-patented inventions and industrial designs.

Furthermore, the principal component regression analysis provides insights into which of the principal components are relevant for predicting the innovation indicator. In the case of patent registrations and non-patented inventions, both principal components are significant and positive. This shows that the higher the codified knowledge stock and the more heterogeneous the tacit knowledge bases through openness to migrations, the greater will be the production of patent registrations and non-patented inventions.

However, in the case of industrial designs applications, the component codified knowledge stock is not significant. This is because only the principal component representing migrations is positive and significant for the dependent variable. The two principal components were found not to be significant for innovations indicators such as trade mark applications and business names applications. This means that neither the codified knowledge component nor the tacit knowledge one was relevant for explaining these two indicators in the form presented.

An interesting observation could be made for the indicators *local mobile employees with more than 5 years of residency*. This indicator is available at local, regional, and national level. The principal component analysis shows that the larger the geographic level (from local to national), the better the alignment with the principal component 2, (i.e. heterogeneous tacit knowledge bases). Local mobile employees are observed to align with the principal component that represents the codified knowledge stock, while regional mobile employees lie somewhere in-between. The interpretation here could be that national migrants bring in new tacit knowledge bases, while local employees contribute only to increasing the codified knowledge stock. Therefore, regional mobile employees contribute to both, tacit knowledge and codified knowledge within the region.

The findings also confirm the role of migrations for innovations that rely especially on tacit knowledge, such as new designs or creative activity. In the case of registered designs, it was only the migration component that explained the dependent variable designs. The import role of openness (especially of migrations) was also confirmed by the high prediction value R-squared on creative workforce in the regions of Europe. Even patents that rely heavily on codified knowledge stock do benefit from a heterogeneous tacit knowledge stock. Both knowledge types are complementary and need to be developed together to increase patenting activity in the regions.

In the first chapter outliers could be observed, suggesting the presence of imbalances between the input and the output variables. For example, the group Finland and Denmark show lower productivity values in relation to their effort in R&D investment. At the same time, these two countries have low non-native population values, an indicator that shows significant correlation with productivity. This suggests that higher values could be achieved if non-native population entered the region.

The subsequent chapter analysed (through principal component regression analysis) the complementary role of the codified knowledge stock and the heterogeneous tacit knowledge bases. Firstly, different openness indicators were selected where it can be observed that migration is the most important openness indicator. The subsequent chapter thus analysed several migration indicators in the Spanish regions to get a comprehensive picture. All in all this research delivers the following responses to the selected hypotheses:

H1: Greater openness in terms of human capital leads to innovativeness

The hypothesis of greater openness through human capital is confirmed in all three chapters. Migrants from outside the country and migrants from outside the region bring in new tacit knowledge bases that are beneficial for the regional innovation system.

H2: A more heterogeneous tacit knowledge base resulting from inward migrations increases the innovation outcome of regional innovation systems.

The hypothesis that migrations lead to a more innovative economy can be confirmed for the great majority of indicators. The hypothesis could not be confirmed in the case of local mobile employees with more than 5 years residency. This indicator aligns with the codified knowledge stock component. Migrations need to take place at least at regional level for them to be able to contribute towards a heterogeneous tacit knowledge base. The indicator local mobile employees with more than 5 years residency, contributes by increasing the codified knowledge stock.

H3: Even though the exchange of external codified knowledge stock needs a good absorptive capacity, openness is also beneficial in terms of innovations for countries and regions with low stocks of codified knowledge.

Hypothesis three could be confirmed for aggregated data at country level. Only countries with very large codified knowledge stocks benefit from international collaborations, whereas all countries benefit from openness.

H4: Greater openness to global sources of human and social capital leads to wider development of creative industries.

The hypothesis that greater openness to global sources of human and social capital leads to creativity seems to be confirmed in this study. Openness results in a heterogeneous tacit knowledge base and can take many forms. Inward migration is the most significant indicator of all openness indicators for increasing the creative workforce in a region. But an inclusive economy is also a tool to open up the labour market and increase heterogeneity of the tacit knowledge base in the case of youth participation in the labour market. This could not be observed for women participation in the labour market.

H5: Openness as a tool to increase heterogeneity of the regional tacit knowledge base is more significant to predict the creative workforce than to predict innovations.

Level of prediction is higher in the principal component regression equation (with creative workforce as dependent variable) than in any of the five regression equations to predict innovations. Therefore, hypothesis five can be confirmed, i.e. openness is more relevant for exploration activities such as creative activities than for exploitation activities such as innovations.

H6: The larger the geographic mobility of migrants in the region, the more the migrants contribute important tacit knowledge.

It could be confirmed that local migrants contribute mainly with codified knowledge, while international migrants contributes with meaningful tacit knowledge. Regional migrants contribute with both, therefore, hypothesis 6 is confirmed; the larger the geographic mobility of migrants, the more they contribute with tacit knowledge.

5.2. Benefits

This thesis has departed from the findings of different research lines and has tried to offer an explanation on why openness is beneficial for creativity and innovation activity in regions. It adds a theory to the creative class literature and to the regional innovation systems literature dealing with knowledge flow at intra-regional level, irrespective of flow in global knowledge pipelines (Bathelt, 2004), global value chains (Schmitz, 2000), or global knowledge networks (Coe et al, 2002).

A theory offers policy makers the possibility to adapt their policies to the specific features of their region with the available instruments and resources. It is not advisable to implement policies that attract the creative class into a region and expect more innovations, without first studying the particulars of the territory. Not all regions can attract the creative class through hip neighbourhoods and an arts scene.

The hypotheses presented in chapter 1.3 tested with a first empirical research in this thesis suggests pursuance of a regional development path. Therefore, a first step should be the development of a regional codified knowledge stock in combination with regionally available tacit knowledge activation.

The study has helped to make the argument that codified and tacit knowledge are input factors which contribute in a complementary manner. This conclusion was reached after performance of a principal component analysis to first ascertain the two components (Openness and R&D Investment) which were then used as input variables in a regression analysis (chapter 3.6.2).

The study methodology can be used for future studies in the different regional and national territories. Given that inward migrations have been the most plausible indicator in activating heterogeneous tacit knowledge pools, the debate on the role of migrations to increase innovations and to make regions more creative could be used in the current debate on large migration flows within Europe. This might help to discuss the potential benefits of these migrants for the development of these regions.

5.3. Position of the thesis in the literature

The present work contributes to earlier works concerning the optimal cognitive distance and the proximity paradox in collaboration activities. By differentiating codified knowledge from tacit knowledge, a different collaboration strategy for innovation was proposed. Nooteboom (2007) demonstrated that cognitive distance is a U-shaped relationship, since an optimal cognitive distance is needed for innovation. Boschma and Broekel (2012) argue the existence of a proximity paradox: While proximity is needed to have high absorptive capacity, cognitive distance is also needed to increase the degree of novelty of the innovation.

The approach of this thesis is to find the optimal cognitive distance by differentiating the knowledge type involved. Cognitive proximity is important when codified knowledge needs to be exchanged, while cognitive distance (i.e. heterogeneous knowledge bases) is important when local tacit knowledge is to be exchanged between the actors involved in a Regional

Innovation System. An increase of cognitive distance in the tacit knowledge base is the result of more heterogeneous tacit knowledge bases being integrated into the regional innovation system.

Therefore, by differentiating knowledge types, this thesis strengthens the argument of Parrilli (2012): Competitive strengths can be reaped not only from highly skilled human capital but also from a broader spectrum of workers who contribute to the tacit knowledge base of a territory. This also matches and deepens the literature on tacit knowledge led by Polanyi, Haruyama and Nonaka (Haruyama, 2009; Nonaka & Krogh, 2009; Polanyi, 1967) and the Regional Innovation Systems literature that deals with the role of tacit knowledge and international knowledge pipelines in Regional Innovation Systems (Bathelt, et al., 2004; Cooke, 1992; Gertler, 2003; Hunt & Gauthier-Loiselle, 2008; Lawson & Lorenz, 1999; Lundvall, et al., 2002; Niebuhr, 2010; Parrilli, 2012), as well as to the creative class literature around Florida (2006).

In an attempt to analyse innovation collaborations in the Dutch aviation industry, Boschma and Broekel (2012) confirmed that a proximity paradox exists for the cognitive and geographic dimension. On the one hand, some cognitive and geographic proximity is needed to exchange knowledge but, on the other hand, if knowledge bases are too similar, the negative effect of a poor novelty value of the innovation outweighs the positive effect of the higher absorptive capacity.

They also confirmed that cognitive distance is more important for exploration activities than for exploitation activities, a distinction that has also been made in this thesis by analysing the effect of openness on creativity, which relates more to exploration activities. Our research confirmed that the principal component regression equation was more accurate in predicting creative workforce than any of the five regression equations that predict innovation.

The main contribution of this thesis is that the proximity literature has been linked with the global knowledge pipelines literature in Regional Innovation Systems and the tacit knowledge literature. Instead of distinguishing proximity along the cognitive, geographic, social, or institutional dimensions, this thesis distinguishes between proximity in tacit and codified knowledge bases, and tries to thus cover all dimensions mentioned by the proximity literature.

This thesis distinguishes internationalisation activities from openness activities despite confirmation of the importance of absorptive capacity in international knowledge pipelines for Regional Innovation Systems (Bathelt, et al., 2004; Cohen & Levinthal, 1990). The main difference of these concepts is related to their role in conveying either codified or tacit knowledge into the regions. Bathelt (2004) considers that codified knowledge can be transported through global knowledge pipelines, where knowledge can be adapted to local interpretations.

However, while some tacit knowledge might be transported into the region through business collaborations with scientists, our hypothesis is that any group of society has its own tacit knowledge, which is unique and valuable (John Kay, 1999; Nonaka & Krogh, 2009; Parrilli, 2012), and that this tacit knowledge is shaped through experiences and interactive practices.

Bathelt (2004) explained that local buzz and global knowledge pipelines offer particular, albeit different, advantages for firms engaged in knowledge creation and innovation. Local buzz is characterised as being spontaneous and an unanticipated interaction of firms.

Therefore, heterogeneous tacit knowledge bases enrich local buzz. Distant collaborations schemes might be possible for specific groups such as scientists but it is very difficult and expensive to open up international collaboration activities to any group within a society. The benefits can only be reaped if these tacit knowledge bases are available at regional level (Lawson & Lorenz, 1999). Since local buzz is characterised as being spontaneous, it is extremely difficult to convey this knowledge through global knowledge pipelines. Moreover, tacit knowledge can only be shared by working together over extended time periods.

This is an argument that is often mentioned in Silicon Valley, where teams are truly international and where an engineer might think of a business application for the rural areas in India. Only through his long-lasting experience of living there, is he/she able to quickly produce an application for a new technological development before others do.

A new theoretical framework to explain meaningful causality has been elaborated based on the above. It is not just creativity that leads to a more open society and it is not only an innovative economy that attracts migrants but the same is also true the other way round. The empirical analysis confirmed that migration leads to higher innovations and creative industries in the regions. For instance, we could observe countries with high innovations, high investments in R&D but low migration values. When compared to other countries, innovation efficiency for these countries is not that high, suggesting that higher migrations lead to higher innovation output.

A heterogeneous society together with high codified knowledge stocks is the ideal combination to create new knowledge. Tacit and codified knowledge are mutually complementary and dynamically interact with each other to create new knowledge. This knowledge conversion process includes a personal subjective knowledge that is socially justified and is brought together with the knowledge of other agents in a way that knowledge keeps expanding (Nonaka & Krogh, 2009).

If we add a heterogeneous tacit knowledge base to a highly codified knowledge stock, the knowledge conversion process produces new heterogeneous and unique knowledge that can be exchanged again. A heterogeneous tacit knowledge base can include a variety of collective values, norms and attitudes of people and workers (Parrilli, 2012), that enrich society by means of greater creativeness and innovativeness.

Hence, this thesis also contributes to the creative class literature developed by Florida and other scholars (Florida, 2006). The creative class literature proved that technology, talent and tolerance are ingredients for successful cities in the U.S. In particular, tolerance is needed to improve openness to alternative lifestyles or, in the words of this thesis, heterogeneous tacit knowledge stocks. Technology and talent are more linked to codified knowledge in this thesis. In a way, the approach of this thesis provides the explanation why the three T's (Technology, Talent, Tolerance) are needed, and in what measure. In this way, better and adjusted policy making in the cities are supported.

5.4. Policy Recommendations:

The results from this thesis contribute by putting forth a series of policy recommendations in the R&D&I field. Policy makers responsible for R&D&I need to take into account the difference between codified knowledge and tacit knowledge and the situation in their region with respect to these knowledge types. While investment to increase codified knowledge is a widespread recommendation to policy makers, opportunities for increasing the innovativeness of the region arise upon bringing in or activating heterogeneous tacit knowledge bases in the region. This research has confirmed that openness is more relevant than internationalisation activities. Establishing international knowledge pipelines is costly and might have an effect of only increasing the codified knowledge stock in the region, which could also be achieved through more cost effective programs.

Internationalisation activities are only recommendable in those fields where sufficient absorptive capacity exists. Developing regions with below average indicators for codified knowledge stock in a specific technology area should promote building up of codified knowledge stock, in order to increase absorptive capacity by reducing their cognitive distance vis-a-vis other regions. Moreover, it is also advisable to increase heterogeneity at regional level and especially in fields where high codified knowledge stock exists. This heterogeneity could be achieved through inward migrations at least at the regional level, high labour flexibility and inclusiveness, by bringing together different genders, ages and groups into the society.

At regional level one can find many ill-matched incentives. There are many barriers to migrations that need to be controlled since they only promote homogenisation of tacit knowledge pools and increase the possibility of knowledge lock-ins and industry myopia. Migration policies should also be developed under the viewpoint of R&D&I targets.

R&D&I policies should target concrete situations in regions on their path towards development. Regional policy makers should first activate the tacit knowledge bases at local level and value inclusiveness not only from the perspective of social justice but also from that of effective R&D&I policies. Of course, not all regions are on the same development path and on the same level as a knowledge-based society. Benefits of R&D&I can only be reaped in the medium and long term while costs are incurred in the short term.

Denmark's regions are an example of successful activation of tacit knowledge pools in their regions. The OECD and many other economic advisory organisations have praised the Danish labour market system, which is very flexible and counterbalances the detrimental effects of flexibility with active labour market policies to increase employability and tight and generous welfare schemes – called Flexicurity (Hendeliowitz, 2008). Many regions and countries cannot offer such generous welfare systems and active labour market policies because they are very expensive in the short term. Moreover, many regions are far from being a knowledge-based economy. The potential benefit would not be the same in regions with large stocks of codified knowledge as in less developed regions. Codified knowledge stock needs to grow with increasing heterogeneous tacit knowledge bases. Therefore, knowledge-based economy (one with a high stock of codified knowledge) is the main beneficiary of a flexible labour market.

The results from this thesis can likewise offer a set of policy recommendations: 1) The first policy recommendation is to implement a Flexicurity system in stages, starting with the R&D&I system. Labour flexibility allows tacit knowledge transfers from one work place to another. A rich, i.e. heterogeneous, tacit knowledge base is especially important in regions with highly codified knowledge stocks. The R&D&I system is a community from within a region with the highest codified knowledge stocks. Labour market flexibility inside the R&D&I system should be especially intensified, to promote exchanges and other forms of mobility schemes. Nevertheless, a very attractive social security network only valid in the R&D&I system should also be put in place in order not to discourage excellence.

2) A second recommendation is to increase heterogeneity in the R&D&I sector, to provide incentives for group variety in the form of ages, gender, ethnic minorities, points of view, and group permeability. A research team or employees in institutions and companies that produce innovations need time for effective collaboration, however, the cognitive distance between the heterogeneous tacit knowledge bases diminishes over time. Therefore, constant renewal is needed. In order to maintain heterogeneity of the tacit knowledge bases, R&D groups need to be permeable; employees need to leave and groups need to be open to new entrants.

3) Thirdly, inward migration has been observed to be the most effective tool to increase heterogeneity of tacit knowledge pools in the region. After achieving an advanced level of codified knowledge stock at aggregate level, emphasis must be placed on incentives to attract inward migrations into the labour market and control of entry-barriers into such market. Migration policies need to work closely together with R&D&I policies under the condition that not only highly qualified research groups can bring tacit knowledge into the region but that the entire society can benefit from a heterogeneous knowledge base that includes less qualified groups. A heterogeneous society therefore attracts further qualified people from outside making the region more appealing.

For instance, there is a high risk that efforts from regions to attract highly skilled people might fail. Dresden is a city with a population of more than half a million but only a low percentage (4.7%) of them are foreigners. Although it was already an important industrial and research centre during the communist government of the German Democratic Republic, the city re-emerged after reunification as a cultural, political, and economic centre in the eastern part of the nation.

In terms of GDP per capita, the city is growing above average and exceeds some poorer German cities in the West, it is now comparable to the overall German average. Dresden has a high percentage of highly qualified employees and hosts very successful research organisations such as the Max Planck Institute for molecular biology and genetics, one of the three Max Planck Institutes, plus 12 Fraunhofer Institutes and universities, among others.

To live up to its excellence the Institute needs to attract the best international researchers. However, Dresden seems to be hostile to immigrants even though their numbers are smaller compared to any other city of its category in Germany. The high-skilled workers working as post-docs within the city feel increasingly uncomfortable, because they feel observed due to their different lifestyles, looks, values, norms, routines, traditions, aptitudes or attitudes which they bring into the city. This situation has been identified as a real threat to the excellence in the region (Agarwala, 2015).

As observed by Parrilli (2012), it seems that a critical mass of heterogeneous social capital is needed as a buffer for inter-ethnic meeting in order to help these people become part of a larger cohesive community. This is a deterrent force that may help to clear threats, derogatory comments and contemptuous looks.

Collaboration programs to exchange these tacit knowledge bases between new entrants and the rest of the society need to be structured and implemented and any form of discrimination needs to be addressed. Bridges need to be developed between the tacit knowledge bases.

4) The last development phase is reached when the economy in the region is largely based on a knowledge-based economy. In this phase, a very flexible labour market should be put in place with active market policies and a level of welfare that the society demands.

A debate on the benefits of migrations for economic development should complement the current European dispute, which mainly seems to focus on the burdens. Moreover, this analysis recommends that migration flows be fostered not only in regions in Spain but also in

European Union regions. A step in that direction could be the integration of the unemployment and social security schemes within the Eurozone, which would also be a step towards a more optimal monetary union (Mundell, 1961). Important benefits for innovation systems can be expected from the resultant rich heterogeneous tacit knowledge bases in the European Union. According to Delanty (2006), who studied cosmopolitan theory in Europe, Europeanisation (i.e. heterogeneous tacit knowledge bases with a common identity) will succeed if it is based on pluralisation and justice rather than on cohesion.

5.5. Shortcomings

The shortcomings of this research are the result of the limited availability of data at regional and local level. There are very large data sets on codified knowledge that cannot be matched with datasets on tacit knowledge bases. As a result, research had to be performed with limited observations which constrain the conclusiveness of the research.

Furthermore, many indicators used to measure tacit knowledge appear to also carry codified knowledge into the region. For instance, any migrant that comes into a region also brings codified knowledge besides tacit knowledge. This could be observed in the migrants in the Spanish communities. Local migrants contribute exclusively to the codified knowledge component but regional migrants contribute to both codified and tacit knowledge, while international migrants contribute to the tacit knowledge component. The first chapter on openness, internationalisation and innovation effectiveness in national innovation systems that served as a basis for the other two chapters partly used indicators such as foreign scientists that also bring codified knowledge into the territory. Moreover, this chapter only included national level data.

Research into the role of migrants as an openness indicator in the Spanish regions showed significant and positive components only in three of the five regression equations.

Furthermore, these three regression equations (where a significant positive role could be confirmed for codified knowledge and migrations) showed rather low values of R^2.

This means that our model only explains a part of the story and there are other significant innovation contributing components that have not been analysed here. Also worth mentioning is that these hypotheses are only applicable in developed regions with stable and strong institutions in place that can assure social justice in a heterogeneous society (Delanty, 2006). Therefore, this research is applicable to the typical region in the European Union with limited migration, strong institutions, and high education standards and an R&D&I system in place.

5.6. Future/open research lines

The thesis has presented a new model to explain the mechanism of how openness leads to more creative industries and innovation activity in the region. It has conducted empirical studies that can lead to multiple research lines in the future. The next step could be to complement these findings with a set of case studies. For instance, a comparison of the results of heterogeneous groups with other more homogenous groups could be done in order to provide useful insights into the interplay between codified knowledge stock and heterogeneous tacit knowledge bases. Another future research line could address the capability of social networks for transferring tacit knowledge bases, in order to seek answers to whether these networks share tacit knowledge and how they could be used in R&D&I policies.

An interesting topic would be to test the hypotheses from a historic perspective, i.e. how regions and countries increase their codified knowledge stock and how this is matched by complementary tacit knowledge bases. The fact that some Danish regions have very flexible and inclusive labour markets and the fact that these policies improved the heterogeneity brought by migrants in other regions seem to suggest that each region has its own way of acquiring the needed heterogeneity of tacit knowledge.

Future research lines could also study the main weakness of this thesis, that is, the resultant inaccuracy due to the limited availability of data sources. Data on mobility and migrations have increased considerably during the time span of this research, and it is likely to increase even more in the future with the growing integration within the Eurozone. Therefore, more data on migrations for instance within the Eurozone and better datasets with higher number of observations could provide more knowledge on the interaction between these two knowledge types. The conclusions from these studies could lead to better decision-making by policy makers in the future (e.g. at the regional level).

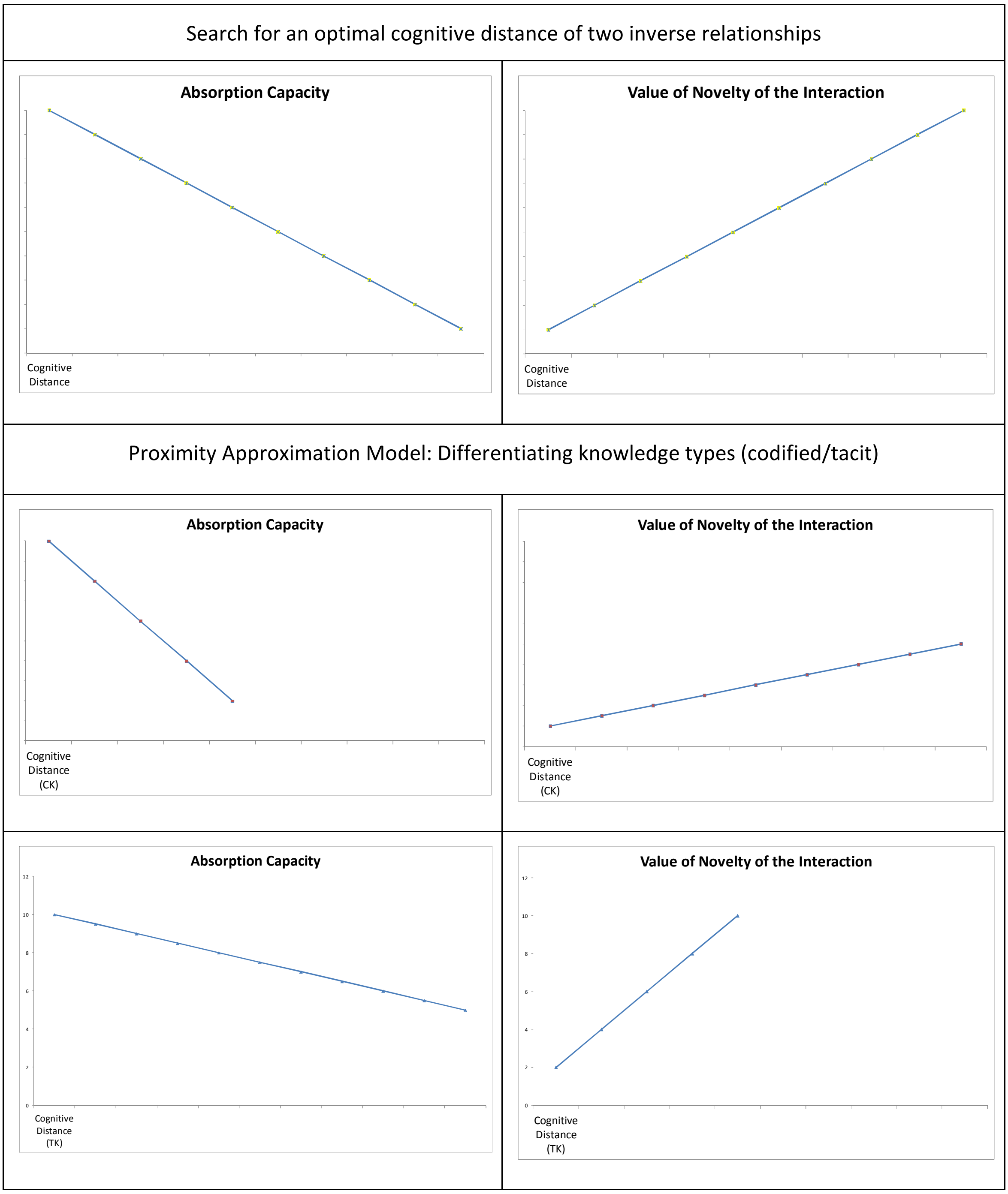
Moreover, future research could analyse different tacit knowledge indicators that have not been analysed or identified here. There are probably more ways of increasing heterogeneity of tacit knowledge bases other than the ones mentioned in this thesis: migrations, inward FDI, foreign companies, flexible labour markets and inclusive labour markets, as well as others that have not been mentioned herein but which could be identified in the future. Therefore, future research should focus on building a better and more accurate tacit knowledge component by including a variety of industries, sectors, mobility of personnel, the effect of bilingual territories, foreign ownership of domestic inventions, etc.

Case studies could also be elaborated at firm level, to for instance, verify whether persons from different departments can physically work together and if innovativeness and creativity is thus enhanced. Many innovation collaboration experiments can be developed between departments in the same firm, at intra-firm level, regional level and at extra-regional level to exchange codified knowledge bases.

Another field of study could be the application of this model and its integration into the creative class literature. The model of the three T's (Talent, Tolerance, Technology) and the optimisation model of the proximity paradox by differentiating codified and tacit knowledge appears to be similar and could therefore be used for further case studies in cities.

Appendix

Figure A1: Absorption capacity and cognitive distance



Source: Own elaboration.

Figure A2: Knowledge creation in the innovation chain

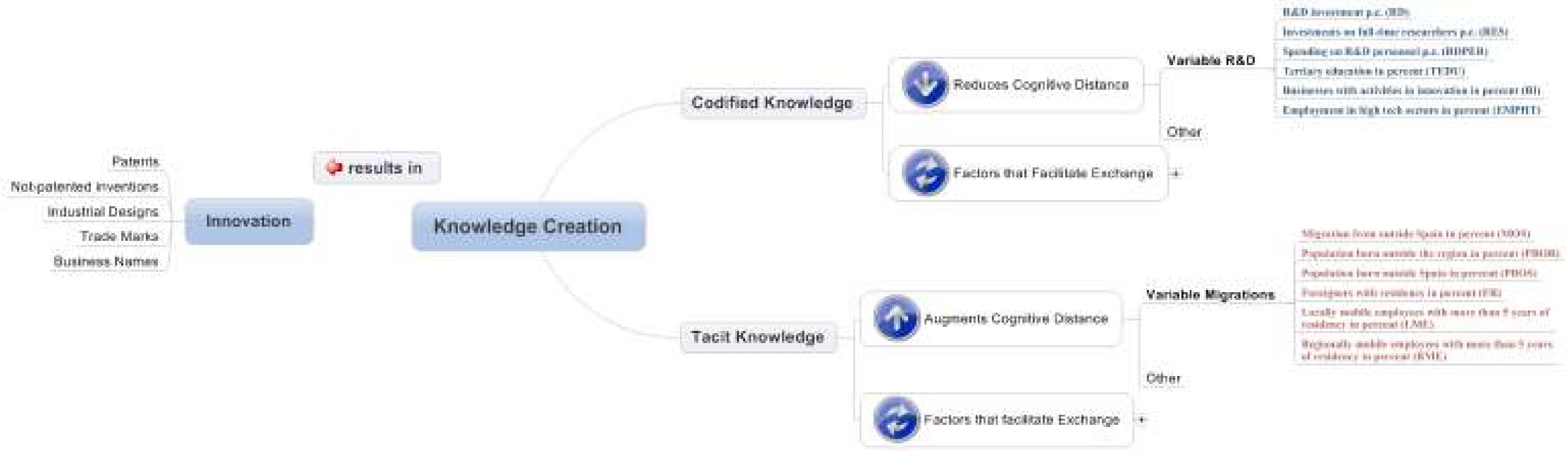


Figure A3: Correlation Coefficients

	I1_IVT	I1_VC-all	I1_Cluster	I2_Non-Native	I2_ForHRSTCore	2_Difemp	I2_Intg1	I2_FDI_in	I3_RD%	I3_R&D pers	I3_HSTpers	I3_ScEngpers	I4_FDI out	I4_Co-Pat	I4_In_Col	I4_RDExt	I4_FP7	I4_DomOwned For.Inv.	O1_Producty	O1_HighExp	O1_HighIm	O1_EmpKnow	O2_Pat	O2_HiPat	O2_VC	O23_Publ	Con_Ind	Con_EmLar	Con_age+65	
I1_IVT	**1,00**	0,52	0,70	0,29	0,23	0,39	0,50	-0,16	0,57	0,50	0,44	0,29	0,30	-0,17	-0,33	0,54	0,08	0,05	0,68	0,18	0,24	0,48	0,63	0,38	0,36	0,47	-0,07	0,13	0,25	**I1_IVT**
I1_VC-all	0,52	**1,00**	0,67	0,39	0,34	0,47	0,66	0,16	0,72	0,69	0,67	0,50	0,46	-0,07	-0,12	0,68	0,35	0,29	0,66	0,29	0,32	0,55	0,68	0,62	0,51	0,57	0,13	0,25	-0,14	**I1_VC-all**
I1_Cluster	0,70	0,67	**1,00**	0,27	0,32	0,53	0,63	0,02	0,79	0,71	0,62	0,56	0,50	-0,10	-0,11	0,59	0,29	0,27	0,82	0,19	0,22	0,57	0,79	0,70	0,51	0,73	0,02	0,19	0,17	**I1_Cluster**
I2_Non-Native	0,29	0,39	0,27	**1,00**	0,73	0,11	0,58	0,41	0,42	0,34	0,47	0,27	0,71	-0,02	-0,16	0,28	0,15	0,42	0,57	0,32	0,34	0,67	0,33	0,11	0,53	0,07	-0,60	-0,16	0,00	**I2_Non-Native**
I2_ForHRSTCore	0,23	0,34	0,32	0,73	**1,00**	0,17	0,60	0,51	0,52	0,43	0,26	0,22	0,78	0,27	-0,17	0,19	0,02	0,63	0,58	0,43	0,44	0,71	0,32	0,08	0,76	0,19	-0,57	0,02	-0,14	**I2_ForHRSTCore**
2_Difemp	0,39	0,47	0,53	0,11	0,17	**1,00**	0,65	0,19	0,61	0,49	0,57	0,56	0,43	-0,21	-0,32	0,60	0,32	0,02	0,56	-0,14	-0,16	0,34	0,66	0,65	0,46	0,65	-0,06	0,30	0,21	**2_Difemp**
I2_Intg1	0,50	0,66	0,63	0,58	0,60	0,65	**1,00**	0,38	0,72	0,61	0,63	0,52	0,72	0,02	-0,40	0,63	0,23	0,37	0,77	0,20	0,23	0,70	0,74	0,56	0,76	0,67	-0,30	0,11	0,09	**I2_Intg1**
I2_FDI_in	-0,16	0,16	0,02	0,41	0,51	0,19	0,38	**1,00**	0,20	0,10	0,25	0,34	0,74	0,20	0,22	0,03	-0,02	0,62	0,31	0,44	0,39	0,52	0,09	0,04	0,44	0,07	-0,28	-0,12	-0,32	**I2_FDI_in**
I3_RD%	0,57	0,72	0,79	0,42	0,52	0,61	0,72	0,20	**1,00**	0,93	0,69	0,71	0,64	0,00	-0,21	0,66	0,34	0,38	0,88	0,30	0,37	0,71	0,91	0,80	0,73	0,75	-0,09	0,19	0,12	**I3_RD%**
I3_R&D pers	0,50	0,69	0,71	0,34	0,43	0,49	0,61	0,10	0,93	**1,00**	0,63	0,57	0,52	-0,07	-0,17	0,65	0,41	0,21	0,77	0,21	0,28	0,62	0,81	0,72	0,63	0,70	-0,05	0,10	0,25	**I3_R&D pers**
I3_HSTpers	0,44	0,67	0,62	0,47	0,26	0,57	0,63	0,25	0,69	0,63	**1,00**	0,71	0,56	-0,28	-0,08	0,56	0,38	0,29	0,68	0,20	0,14	0,63	0,69	0,69	0,47	0,54	-0,18	0,03	0,02	**I3_HSTpers**
I3_ScEngpers	0,29	0,50	0,56	0,27	0,22	0,56	0,52	0,34	0,71	0,57	0,71	**1,00**	0,65	0,10	-0,05	0,45	0,33	0,37	0,72	0,25	0,30	0,60	0,65	0,73	0,58	0,64	-0,08	0,22	-0,10	**I3_ScEngpers**
I4_FDI out	0,30	0,46	0,50	0,71	0,78	0,43	0,72	0,74	0,64	0,52	0,56	0,65	**1,00**	0,23	-0,01	0,34	0,14	0,63	0,79	0,39	0,43	0,82	0,50	0,36	0,78	0,44	-0,46	0,06	-0,12	**I4_FDI out**
I4_Co-Pat	-0,17	-0,07	-0,10	-0,02	0,27	-0,21	0,02	0,20	0,00	-0,07	-0,28	0,10	0,23	**1,00**	0,35	-0,11	-0,52	0,25	0,01	-0,01	0,17	-0,02	-0,13	-0,19	0,18	0,04	0,12	0,45	-0,39	**I4_Co-Pat**
I4_In_Col	-0,33	-0,12	-0,11	-0,16	-0,17	-0,32	-0,40	0,22	-0,21	-0,17	-0,08	-0,05	-0,01	0,35	**1,00**	-0,18	-0,25	0,08	-0,25	-0,06	-0,08	-0,24	-0,25	-0,13	-0,33	-0,24	0,32	-0,03	-0,21	**I4_In_Col**
I4_RDExt	0,54	0,68	0,59	0,28	0,19	0,60	0,63	0,03	0,66	0,65	0,56	0,45	0,34	-0,11	-0,18	**1,00**	0,51	0,10	0,61	0,11	0,11	0,48	0,67	0,65	0,35	0,71	-0,01	0,11	0,14	**I4_RDExt**
I4_FP7	0,08	0,35	0,29	0,15	0,02	0,32	0,23	-0,02	0,34	0,41	0,38	0,33	0,14	-0,52	-0,25	0,51	**1,00**	0,06	0,29	0,08	-0,06	0,26	0,36	0,48	0,12	0,40	-0,19	-0,27	0,22	**I4_FP7**
I4_DomOwned For. Inv.	0,05	0,29	0,27	0,42	0,63	0,02	0,37	0,62	0,38	0,21	0,29	0,37	0,63	0,25	0,08	0,10	0,06	**1,00**	0,50	0,76	0,62	0,68	0,25	0,19	0,43	0,14	-0,41	-0,26	-0,57	**I4_DomOwned For. Inv.**
O1_Producty	0,68	0,66	0,82	0,57	0,58	0,56	0,77	0,31	0,88	0,77	0,68	0,72	0,79	0,01	-0,25	0,61	0,29	0,50	**1,00**	0,40	0,46	0,85	0,80	0,65	0,73	0,71	-0,30	0,09	0,05	**O1_Producty**
O1_HighExp	0,18	0,29	0,19	0,32	0,43	-0,14	0,20	0,44	0,30	0,21	0,20	0,25	0,39	-0,01	-0,06	0,11	0,08	0,76	0,40	**1,00**	0,88	0,67	0,19	0,15	0,31	0,04	-0,29	-0,38	-0,41	**O1_HighExp**
O1_HighIm	0,24	0,32	0,22	0,34	0,44	-0,16	0,23	0,39	0,37	0,28	0,14	0,30	0,43	0,17	-0,08	0,11	-0,06	0,62	0,46	0,88	**1,00**	0,62	0,23	0,16	0,42	0,18	-0,09	-0,11	-0,41	**O1_HighIm**
O1_EmpKnow	0,48	0,55	0,57	0,67	0,71	0,34	0,70	0,52	0,71	0,62	0,63	0,60	0,82	-0,02	-0,24	0,48	0,26	0,68	0,85	0,67	0,62	**1,00**	0,61	0,47	0,73	0,45	-0,48	-0,09	-0,07	**O1_EmpKnow**
O2_Pat	0,63	0,68	0,79	0,33	0,32	0,66	0,74	0,09	0,91	0,81	0,69	0,65	0,50	-0,13	-0,25	0,67	0,36	0,25	0,80	0,19	0,23	**0,61**	**1,00**	0,87	0,58	0,75	0,03	0,20	0,30	**O2_Pat**
O2_HiPat	0,38	0,62	0,70	0,11	0,08	0,65	0,56	0,04	0,80	0,72	0,69	0,73	0,36	-0,19	-0,13	0,65	0,48	0,19	0,65	0,15	0,16	0,47	0,87	**1,00**	0,49	0,79	0,11	0,19	0,20	**O2_HiPat**
O2_VC	0,36	0,51	0,51	0,53	0,76	0,46	0,76	0,44	0,73	0,63	0,47	0,58	0,78	0,18	-0,33	0,35	0,12	0,43	0,73	0,31	0,42	0,73	0,58	0,49	**1,00**	0,59	-0,38	0,24	0,02	**O2_VC**
O23_Publ	0,47	0,57	0,73	0,07	0,19	0,65	0,67	0,07	0,75	0,70	0,54	0,64	0,44	0,04	-0,24	0,71	0,40	0,14	0,71	0,04	0,18	0,45	0,75	0,79	0,59	**1,00**	0,08	0,28	0,14	**O23_Publ**
Con_Ind	-0,07	0,13	0,02	-0,60	-0,57	-0,06	-0,30	-0,28	-0,09	-0,05	-0,18	-0,08	-0,46	0,12	0,32	-0,01	-0,19	-0,41	-0,30	-0,29	-0,09	-0,48	0,03	0,11	-0,38	0,08	**1,00**	0,50	-0,06	**Con_Ind**
Con_EmLar	0,13	0,25	0,19	-0,16	0,02	0,30	0,11	-0,12	0,19	0,10	0,03	0,22	0,06	0,45	-0,03	0,11	-0,27	-0,26	0,09	-0,38	-0,11	-0,09	0,20	0,19	0,24	0,28	0,50	**1,00**	-0,03	**Con_EmLar**
Con_age+65	0,25	-0,14	0,17	0,00	-0,14	0,21	0,09	-0,32	0,12	0,25	0,02	-0,10	-0,12	-0,39	-0,21	0,14	0,22	-0,57	0,05	-0,41	-0,41	-0,07	0,30	0,20	0,02	0,14	-0,06	-0,03	**1,00**	**Con_age+65**
	I1_IVT	I1_VC-all	I1_Cluster	I2_Non-Native	I2_ForHRSTCore	2_Difemp	I2_Intg1	I2_FDI_in	I3_RD%	I3_R&D pers	I3_HSTpers	I3_ScEngpers	I4_FDI out	I4_Co-Pat	I4_In_Col	I4_RDExt	I4_FP7	I4_DomOwned For.Inv.	O1_Producty	O1_HighExp	O1_HighIm	O1_EmpKnow	O2_Pat	O2_HiPat	O2_VC	O23_Publ	Con_Ind	Con_EmLar	Con_age+65	

Figure A4: Significance Values of the Correlation Coefficients

	I1_IVT	I1_VC-all	I1_Cluster	I2_Non-Native	I2_ForHRSTCore	2_Difemp	I2_Intg1	I2_FDI_in	I3_RD%	I3_R&D pers	I3_HSTpers	I3_ScEngpers	I4_FDI out	I4_Co-Pat	I4_In_Col	I4_RDExt	I4_FP7	I4_DomOwned For.Inv.	O1_Producty	O1_HighExp	O1_HighIm	O1_EmpKnow	O2_Pat	O2_HiPat	O2_VC	O23_Publ	Con_Ind	Con_EmLar	Con_age+65	
I1_IVT		0.0042	0.0000	0.1400	0.2467	0.0387	0.0070	0.4053	0.0015	0.0068	0.0187	0.1303	0.1250	0.3775	0.0914	0.0028	0.6873	0.7954	0.0000	0.3504	0.2130	0.0105	0.0003	0.0472	0.0586	0.0110	0.7162	0.5247	0.1945	I1_IVT
I1_VC-all	0.0042		0.0001	0.0428	0.0804	0.0115	0.0002	0.4123	0.0000	0.0000	0.0000	0.0071	0.0142	0.7386	0.5492	0.0000	0.0669	0.1378	0.0002	0.1359	0.0947	0.0026	0.0000	0.0004	0.0058	0.0016	0.5179	0.2076	0.4706	I1_VC-all
I1_Cluster	0.0000	0.0001		0.1664	0.0990	0.0039	0.0003	0.9141	0.0000	0.0000	0.0004	0.0021	0.0073	0.6045	0.5819	0.0009	0.1400	0.1604	0.0000	0.3391	0.2531	0.0015	0.0000	0.0000	0.0060	0.0000	0.9088	0.3206	0.3845	I1_Cluster
I2_Non-Native	0.1400	0.0428	0.1664		0.0000	0.5741	0.0014	0.0285	0.0268	0.0736	0.0112	0.1627	0.0000	0.9104	0.4055	0.1508	0.4330	0.0245	0.0014	0.0977	0.0776	0.0001	0.0841	0.5709	0.0034	0.7125	0.0007	0.4172	0.9957	I2_Non-Native
I2_ForHRSTCore	0.2467	0.0804	0.0990	0.0000		0.3843	0.0007	0.0051	0.0048	0.0207	0.1881	0.2586	0.0000	0.1657	0.3742	0.3383	0.9192	0.0004	0.0011	0.0230	0.0193	0.0000	0.0995	0.6912	0.0000	0.3403	0.0014	0.9381	0.4837	I2_ForHRSTCore
2_Difemp	0.0387	0.0115	0.0039	0.5741	0.3843		0.0002	0.3334	0.0005	0.0079	0.0016	0.0021	0.0238	0.2818	0.0922	0.0007	0.1024	0.9087	0.0021	0.4635	0.4236	0.0783	0.0001	0.0002	0.0136	0.0002	0.7595	0.1268	0.2871	2_Difemp
I2_Intg1	0.0070	0.0002	0.0003	0.0014	0.0007	0.0002		0.0490	0.0000	0.0005	0.0004	0.0043	0.0000	0.9093	0.0352	0.0003	0.2426	0.0531	0.0000	0.3188	0.2479	0.0000	0.0000	0.0021	0.0000	0.0001	0.1214	0.5634	0.6603	I2_Intg1
I2_FDI_in	0.4053	0.4123	0.9141	0.0285	0.0051	0.3334	0.0490		0.3109	0.6295	0.2073	0.0749	0.0000	0.2983	0.2557	0.8789	0.9353	0.0004	0.1055	0.0194	0.0415	0.0047	0.6526	0.8356	0.0190	0.7100	0.1421	0.5364	0.0989	I2_FDI_in
I3_RD%	0.0015	0.0000	0.0000	0.0268	0.0048	0.0005	0.0000	0.3109		0.0000	0.0000	0.0000	0.0002	0.9920	0.2744	0.0001	0.0733	0.0453	0.0000	0.1187	0.0523	0.0000	0.0000	0.0000	0.0000	0.0000	0.6352	0.3296	0.5444	I3_RD%
I3_R&D pers	0.0068	0.0000	0.0000	0.0736	0.0207	0.0079	0.0005	0.6295	0.0000		0.0003	0.0014	0.0045	0.7154	0.3781	0.0002	0.0285	0.2889	0.0000	0.2722	0.1518	0.0004	0.0000	0.0000	0.0003	0.0000	0.7816	0.6096	0.1912	I3_R&D pers
I3_HSTpers	0.0187	0.0000	0.0004	0.0112	0.1881	0.0016	0.0004	0.2073	0.0000	0.0003		0.0000	0.0019	0.1448	0.6994	0.0019	0.0448	0.1391	0.0000	0.3074	0.4809	0.0003	0.0000	0.0000	0.0122	0.0030	0.3643	0.8862	0.9390	I3_HSTpers
I3_ScEngpers	0.1303	0.0071	0.0021	0.1627	0.2586	0.0021	0.0043	0.0749	0.0000	0.0014	0.0000		0.0002	0.6007	0.8147	0.0159	0.0842	0.0526	0.0000	0.1927	0.1180	0.0008	0.0002	0.0000	0.0014	0.0003	0.6684	0.2653	0.6064	I3_ScEngpers
I4_FDI out	0.1250	0.0142	0.0073	0.0000	0.0000	0.0238	0.0000	0.0000	0.0002	0.0045	0.0019	0.0002		0.2340	0.9593	0.0783	0.4817	0.0003	0.0000	0.0399	0.0217	0.0000	0.0064	0.0565	0.0000	0.0205	0.0141	0.7697	0.5567	I4_FDI out
I4_Co-Pat	0.3775	0.7386	0.6045	0.9104	0.1657	0.2818	0.9093	0.2983	0.9920	0.7154	0.1448	0.6007	0.2340		0.0651	0.5602	0.0049	0.1937	0.9568	0.9490	0.3845	0.9360	0.5177	0.3443	0.3601	0.8342	0.5389	0.0164	0.0388	I4_Co-Pat
I4_In_Col	0.0914	0.5492	0.5819	0.4055	0.3742	0.0922	0.0352	0.2557	0.2744	0.3781	0.6994	0.8147	0.9593	0.0651		0.3582	0.2012	0.6807	0.2036	0.7697	0.6832	0.2133	0.1924	0.5204	0.0911	0.2216	0.0922	0.8909	0.2934	I4_In_Col
I4_RDExt	0.0028	0.0000	0.0009	0.1508	0.3383	0.0007	0.0003	0.8789	0.0001	0.0002	0.0019	0.0159	0.0783	0.5602	0.3582		0.0060	0.6037	0.0006	0.5704	0.5783	0.0103	0.0000	0.0002	0.0638	0.0000	0.9516	0.5662	0.4748	I4_RDExt
I4_FP7	0.6873	0.0669	0.1400	0.4330	0.9192	0.1024	0.2426	0.9353	0.0733	0.0285	0.0448	0.0842	0.4817	0.0049	0.2012	0.0060		0.7506	0.1388	0.6806	0.7654	0.1733	0.0624	0.0089	0.5533	0.0334	0.3433	0.1578	0.2601	I4_FP7
I4_DomOwned For. Inv.	0.7954	0.1378	0.1604	0.0245	0.0004	0.9087	0.0531	0.0004	0.0453	0.2889	0.1391	0.0526	0.0003	0.1937	0.6807	0.6037	0.7506		0.0068	0.0000	0.0004	0.0000	0.2075	0.3374	0.0217	0.4648	0.0282	0.1857	0.0014	I4_DomOwned For. Inv.
O1_Producty	0.0000	0.0002	0.0000	0.0014	0.0011	0.0021	0.0000	0.1055	0.0000	0.0000	0.0000	0.0000	0.0000	0.9568	0.2036	0.0006	0.1388	0.0068		0.0362	0.0133	0.0000	0.0000	0.0002	0.0000	0.0000	0.1163	0.6363	0.8058	O1_Producty
O1_HighExp	0.3504	0.1359	0.3391	0.0977	0.0230	0.4635	0.3188	0.0194	0.1187	0.2722	0.3074	0.1927	0.0399	0.9490	0.7697	0.5704	0.6806	0.0000	0.0362		0.0000	0.0000	0.3422	0.4526	0.1044	0.8260	0.1340	0.0481	0.0298	O1_HighExp
O1_HighIm	0.2130	0.0947	0.2531	0.0776	0.0193	0.4236	0.2479	0.0415	0.0523	0.1518	0.4809	0.1180	0.0217	0.3845	0.6832	0.5783	0.7654	0.0004	0.0133	0.0000		0.0004	0.2317	0.4087	0.0269	0.3556	0.6544	0.5691	0.0307	O1_HighIm
O1_EmpKnow	0.0105	0.0026	0.0015	0.0001	0.0000	0.0783	0.0000	0.0047	0.0000	0.0004	0.0003	0.0008	0.0000	0.9360	0.2133	0.0103	0.1733	0.0000	0.0000	0.0000	0.0004		0.0005	0.0124	0.0000	0.0153	0.0105	0.6664	0.7421	O1_EmpKnow
O2_Pat	0.0003	0.0000	0.0000	0.0841	0.0995	0.0001	0.0000	0.6526	0.0000	0.0000	0.0000	0.0002	0.0064	0.5177	0.1924	0.0000	0.0624	0.2075	0.0000	0.3422	0.2317	**0.0005**		0.0000	0.0011	0.0000	0.8705	0.2957	0.1230	O2_Pat
O2_HiPat	0.0472	0.0004	0.0000	0.5709	0.6912	0.0002	0.0021	0.8356	0.0000	0.0000	0.0000	0.0000	0.0565	0.3443	0.5204	0.0002	0.0089	0.3374	0.0002	0.4526	0.4087	0.0124	0.0000		0.0079	0.0000	0.5801	0.3228	0.2957	O2_HiPat
O2_VC	0.0586	0.0058	0.0060	0.0034	0.0000	0.0136	0.0000	0.0190	0.0000	0.0003	0.0122	0.0014	0.0000	0.3601	0.0911	0.0638	0.5533	0.0217	0.0000	0.1044	0.0269	0.0000	0.0011	0.0079		0.0009	0.0472	0.2220	0.9116	O2_VC
O23_Publ	0.0110	0.0016	0.0000	0.7125	0.3403	0.0002	0.0001	0.7100	0.0000	0.0000	0.0030	0.0003	0.0205	0.8342	0.2216	0.0000	0.0334	0.4648	0.0000	0.8260	0.3556	0.0153	0.0000	0.0000	0.0009		0.6901	0.1544	0.4766	O23_Publ
Con_Ind	0.7162	0.5179	0.9088	0.0007	0.0014	0.7595	0.1214	0.1421	0.6352	0.7816	0.3643	0.6684	0.0141	0.5389	0.0922	0.9516	0.3433	0.0282	0.1163	0.1340	0.6544	0.0105	0.8705	0.5801	0.0472	0.6901		0.0069	0.7799	Con_Ind
Con_EmLar	0.5247	0.2076	0.3206	0.4172	0.9381	0.1268	0.5634	0.5364	0.3296	0.6096	0.8862	0.2653	0.7697	0.0164	0.8909	0.5662	0.1578	0.1857	0.6363	0.0481	0.5691	0.6664	0.2957	0.3228	0.2220	0.1544	0.0069		0.8646	Con_EmLar
Con_age+65	0.1945	0.4706	0.3845	0.9957	0.4837	0.2871	0.6603	0.0989	0.5444	0.1912	0.9390	0.6064	0.5567	0.0388	0.2934	0.4748	0.2601	0.0014	0.8058	0.0298	0.0307	0.7421	0.1230	0.2957	0.9116	0.4766	0.7799	0.8646		Con_age+65
	I1_IVT	I1_VC-all	I1_Cluster	I2_Non-Native	I2_ForHRSTCore	2_Difemp	I2_Intg1	I2_FDI_in	I3_RD%	I3_R&D pers	I3_HSTpers	I3_ScEngpers	I4_FDI out	I4_Co-Pat	I4_In_Col	I4_RDExt	I4_FP7	I4_DomOwned For.Inv.	O1_Producty	O1_HighExp	O1_HighIm	O1_EmpKnow	O2_Pat	O2_HiPat	O2_VC	O23_Publ	Con_Ind	Con_EmLar	Con_age+65	

Figure A5: Correlations and Significance Values 2012

Correlations & Significance Values 2012																																
Correlation	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
	Sp.Int.migr.totl_	**Sp.Int.migr.forg..**	**Sp.Int.migr.nat...**	**Sp.ext.migr.totl..**	**Bal.ext.migr.totl..**	**Regs.var.Sp..**	**Intr.region.migr.Sp..**	**Born.dist.CC.AA_**	**Born.dist.Prov._**	**Born.dist.ctry_**	**Forg.._**	**Var.forg_**	**Forg.in.CC.AA._**	**Lab.Mob.Loc_.1_**	**Lab.Mob.Loc_1.3_**	**Lab.Mob.Loc_3.5_**	**Lab.Mob.Loc_.5_**	**Lab.Mob.Region_.1_**	**Lab.Mob.Region_1.3_**	**Lab.Mob.Region_3.5_**	**Lab.Mob.Region_.5_**	**Pop.Change_**	**R.D_p.c.**	**R.D_pers_P.c.**	**I_EIC_p.c.**	**R.D_bus_p.c.**	**Pers_R.D_EJC_p.c.**	**I_EIC.Bus_p.c.**	**Tert_Edu_**	**Inn.Act_Bus_p.c.**	**EIN.Bus_p.c.**	**HT.Employ_**
Patents_INE_p.c.	0,05	0,4	-0,1	0,05	-0,6	0,02	0	0,4	0,3	0,2	0,28	-0,2	0,03	0,39	0,43	0,44	0,62	0,06	0,53	0,45	0,47	-0,3	0,55	0,67	0,68	0,52	0,55	0,49	0,59	0,75	0,75	0,41
Utility_INE_p.c.	-0,2	0,32	-0,4	0,08	-0,8	-0,1	-0,2	0,43	0,03	0,22	0,28	-0,1	0,03	0,34	0,4	0,36	0,46	0,04	0,47	0,31	0,4	-0,5	0,54	0,65	0,62	0,49	0,55	0,5	0,5	0,83	0,62	0,51
Design_INE_p.c.	0,36	0,35	0,31	0,66	-0,2	0,39	0,36	0,38	0,34	0,78	0,71	0,1	0,77	0,4	0,26	0,43	0,05	0,39	0,17	0,07	0,4	0,32	-0,1	0,06	0,07	-0,1	-0	-0	-0,1	0,35	0,06	0,13
Brands_INE_p.c.	0,25	0,21	0,22	0,54	-0,5	0,38	0,21	0,6	0,59	0,55	0,51	-0,1	0,49	0,63	0,7	0,67	0,43	0,3	0,53	0,32	0,56	0,01	0,41	0,49	0,46	0,32	0,36	0,33	0,46	0,49	0,33	0,69
Bus_Names_INE_p.c.	0,26	0,01	0,31	0,43	-0,2	0,33	0,25	0,32	0,50	0,42	0,33	-0,2	0,41	0,32	0,4	0,49	-0	0,25	0,28	0,3	0,32	0,11	0,1	0,12	0,07	0,02	0	-0	0,09	0,12	-0	0,37
Productivity.change	-0,5	-0,2	-0,5	-0,4	0	-0,5	-0,5	-0,5	-0,5	-0,4	-0,4	0,19	-0,4	-0,2	-0,4	-0,4	0,25	-0,4	-0,3	-0,3	-0,4	-0,3	0,11	0,17	0,19	0,19	0,22	0,21	0,05	0,24	0,32	-0,3
P-Value (Significance Values)																																
Patents_INE_p.c.	0,85	0,11	0,71	0,84	0,01	0,93	1,00	0,11	0,25	0,45	0,28	0,37	0,92	0,13	0,08	0,07	0,01	0,83	0,03	0,07	0,06	0,23	0,02	0,00	0,00	0,03	0,02	0,05	0,01	0,00	0,00	0,10
Utility_INE_p.c.	0,48	0,20	0,16	0,76	0,00	0,64	0,38	0,09	0,92	0,40	0,27	0,63	0,90	0,18	0,12	0,15	0,06	0,87	0,06	0,23	0,11	0,04	0,03	0,00	0,01	0,05	0,02	0,04	0,04	0,00	0,01	0,04
Design_INE_p.c.	0,15	0,17	0,22	0,00	0,44	0,12	0,16	0,14	0,19	0,00	0,00	0,71	0,00	0,11	0,31	0,08	0,86	0,12	0,51	0,79	0,12	0,21	0,84	0,83	0,78	0,71	0,88	0,87	0,86	0,17	0,82	0,61
Brands_INE_p.c.	0,34	0,41	0,39	0,02	0,03	0,14	0,42	0,01	0,01	0,02	0,04	0,67	0,05	0,01	0,00	0,00	0,08	0,24	0,03	0,20	0,02	0,97	0,10	0,04	0,06	0,21	0,16	0,19	0,06	0,05	0,20	0,00
Bus_Names_INE_p.c.	0,32	0,98	0,22	0,09	0,51	0,19	0,33	0,20	0,04	0,09	0,20	0,45	0,10	0,21	0,11	0,04	0,95	0,34	0,27	0,24	0,21	0,66	0,72	0,65	0,78	0,95	1,00	0,94	0,72	0,65	0,89	0,14
Productivity.change	0,04	0,46	0,02	0,09	0,98	0,07	0,04	0,06	0,06	0,12	0,15	0,45	0,09	0,38	0,09	0,13	0,34	0,15	0,26	0,20	0,09	0,30	0,66	0,52	0,47	0,47	0,40	0,42	0,84	0,36	0,21	0,30

Figure A6: Heterogeneity across regions of variable Creative Workforce

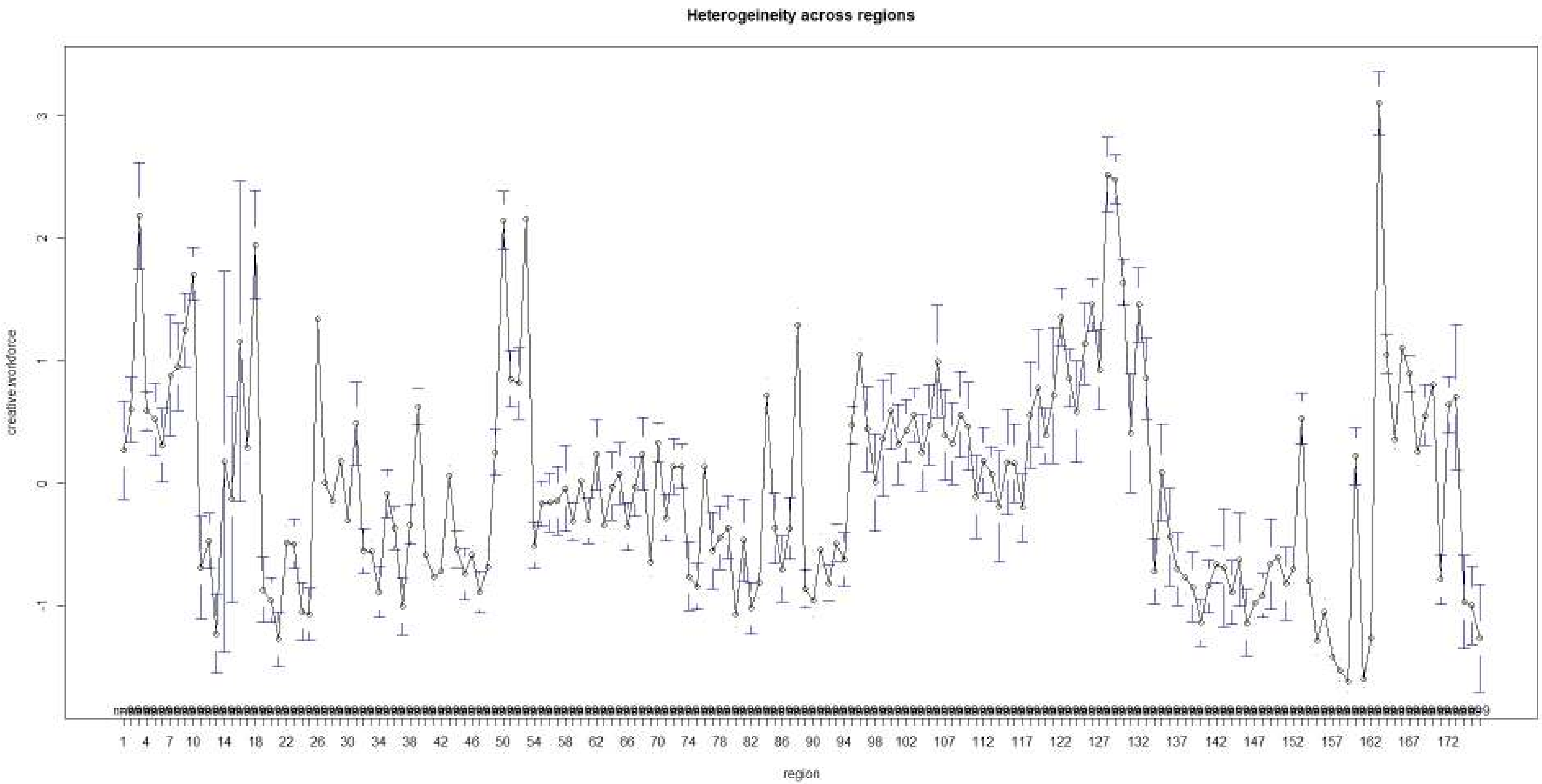
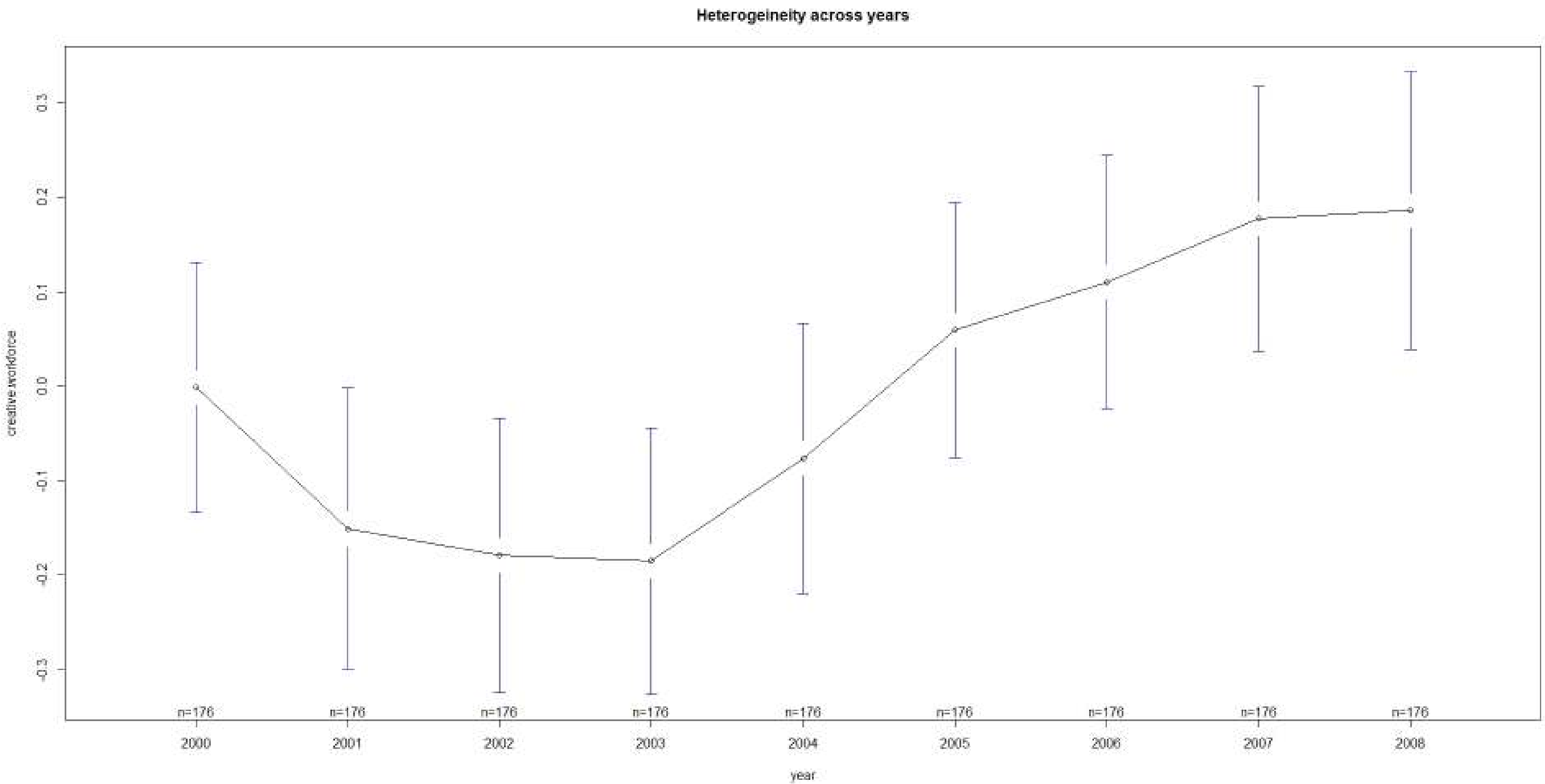


Figure A7: Heterogeneity across years of variable Creative Workforce



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