MASTER THESIS

Towards Stronger Clusters in Europe

ERASMUS UNIVERSITY ROTTERDAM
Faculty of Economics of Business
Entrepreneurship, Strategy and Organisation Economics
Supervisor: Dr. S. M. W. Phlippen
Name: Chantal Presilli
Exam number: 314737
Email address: 314737cp@student.eur.nl

Table of contents

Abstract

This thesis studies the effect of cluster strength on the cluster performance related to innovation and export. The role of cluster strength is discussed in the theoretical framework. Based on this theoretical framework, four hypotheses are derived. The first one assumes cluster-strength to have a positive effect on innovation. The second one assumes cluster strength to have a positive effect on export. The theoretical framework is applied to the pharmaceutical and automotive sector. The pharmaceutical sector is expected to have stronger innovative cluster performance than other industrial sectors. Automotive sector is expected to have stronger export performance than other industrial sectors.

A dataset has been constructed containing cluster data from 2007. Using a binary logistic regression model and an ordinal logistic regression model, the effects of cluster strength on innovation and export are researched. Three cluster indicators are used to measure the effect of cluster strength, namely: cluster size, cluster focus and cluster specialization. Next to this, cluster dummies, industry dummies and country dummies are added to the model. Results show that there is a significant relationship between cluster strength and the dependent variables in de model. All hypotheses are accepted. The research pointed out that there is a positive relationship between cluster strength and innovation. Further, the results of the research show a positive influence of cluster strength on export. Clusters related to the automotive industry have higher export and innovation performances than other industrial clusters in the model. As well as the automotive industry, the pharmaceutical industry has higher cluster innovation performance than other industrial clusters in the model.

1. Introduction

1.1 European cluster policy

In the last decade cluster policy has become an important focus for the European Commission. In the report "Putting knowledge into action" the European Commission states that Europe has to become more inventive and firms have to respond better to consumer needs. Clusters seem to be the obvious means for achieving the policy goals (European Commission, 2006b). One of the objectives of the European Commission is to promote clusters "*by strengthening the knowledge base in Europe and enabling better exploitation of research for innovation*"(European Commission 2007, p 22). It is suggested that Europe has become a stable environment after the Second World War, where its inhabitants are risk averse and reluctant to change (European Commission, 2006a). This causes, amongst others, an arrear in economic performance in the face of the rising competition from other places in the world, like the United States and Japan. As a result a European policy program aimed at stronger industrial clusters has been launched.

Clusters are important for the economic performance. Several causes can be pointed out related to this. For example, global competition triggers large corporations to outsource their production so they can specialize in production. Due to competition, large corporations tend to reduce in-house production and administrative costs, when they increase outsourcing and learning. Thus, firms become more specialized, which makes location in clusters more attractive. It gets more attractive to be located near partners, as firms can easily identify each other and work together if they are co-located (European Commission, 2006a; Oxford Research AS, 2008). It important to notice that outsourcing does not only take place on a firm-to-firm level but also between firms and public institutions, like universities and research centers (Porter, 2007). Porter (2007) assumes that regarding the need for interaction, firms co-locate as all economic actors are represented in clusters.

In the second place, innovation contributes to the important role of clusters. Small knowledge based firms close to universities are further up in the technological learning curve. A technological learning curve is an experience curve which presumes that the firm with the greatest cumulative production experience enjoys the most advantage over rivals (Lieberman, 1989). This means that the basis of industrial competitiveness is dynamic improvement, which benefits firms that are able to create knowledge faster than competitors. There is a difference of opinion in the literature about how clusters and innovation are related (e.g. Marshall, 1920, Jacobs, 1969, Porter, 2003). Marshall (1920) argues that knowledge is created in regional learning curves. According to him the most important knowledge-spillovers occur among firms within the same industry. The learning curves are regional as every locality has its own capabilities which affect the industry that is carried on in it. Highly specialized locations experience higher levels of innovation. On the contrary, Jacobs (1969) emphasizes the diversity of clusters. Due to diversity firms have opportunities to be creative and innovative, as firms can combine knowledge from different fields (Madsen et al., 2004). Porter (2003) represents a third view; it is a theory which is between the two extremes of Marshall and Jacobs. Porter argues that knowledge-spillovers occur in clusters of related industries. He emphasizes intense competition within clusters. Competition increases the innovative capability and incentives to develop products and production processes. Innovation is indispensible as it improves the individual well being through more intelligent infrastructure provision. European environment needs to be protected by way of innovation, because innovation will strengthen Europe's position in the global competition (Cooke, 2001).

1.2 Research questions

European policymakers try to compete by means of cluster strength with high developed clusters from elsewhere. First will be discussed how cluster strength is measured by the European Commission (European Commission, 2007). The definition given by the European Commission will be used for cluster strength in this research. The European Commission has constructed three indicators for which European clusters can receive a star. These indicators will also be used in this research to create a dataset with clusters with one, two and three stars. As the research is focused on the European clusters and the role of European policymakers in promoting these clusters, the cluster will be ordered in the same way as the European Commission has ordered the clusters. This is why clusters with no stars are left out of the data. The first indicator is cluster size. To calculate cluster size, all the clusters are ranked by employment-size. The first 26 clusters with the highest employment-size receive a star. The second indicator is cluster focus. This ratio relates employment in the cluster to the total employment in the region. The highest ten percent for each industry receive a star. The last indicator is cluster specialization. This ratio relates cluster focus to the ratio of European employment in the same industry compared to the total European employment. The indicators are further explained in chapter 3. At best, clusters can score three stars. This paper aims to clarify the role of stronger clusters in Europe. As explained above, European policymakers are focused on creating stronger clusters in Europe. This is why this research compares the cluster performance of strong clusters, containing two and three stars, with the cluster performance of weaker clusters, containing only one star.

As discussed above, the motive for studying the role of strong clusters in Europe is the pro-active attitude of European policymakers towards cluster policies (European Commission, 2006b and European Commission, 2006a). The stand in literature on the effectiveness of cluster policy seems to be dispersed (e.g. Cooke, 2001; Brenner, 2004; and Lindqvist, 2009). Some authors argue for a pro-active cluster policy while others are reluctant for a prominent cluster policy, because of failures of many policymakers in creating clusters. Besides this there is a high diversity among European member states in terms of economic activity. Given the European diversity, national and regional policies are even more important than a European policy because different regions need a different kind of policy approach. This raises the first research question addressed in the paper, which will be discussed in paragraph 2.2:

How do national and regional policies influence cluster strength?

To answer the above mentioned research question the following sub-questions are set out:

- On what kind of levels is cluster policy implemented?
- What kinds of policy targets are effective?

The European policy target is to improve the creation of new markets, provision of sufficient recourses and adaptability of Europe, which according to the European Commission can be accomplished through high levels of innovation and trade (European Commission, 2006a). The Commission demonstrates a positive correlation between the share of employees in clusters and prosperity level, in terms of GDP per Capita (European Commission, 2007). This raises the second research question addressed in the paper, which will be discussed in paragraph 2.2 and 2.3:

Do stronger clusters entail higher innovation and export rates?

To answer the second research question the following sub-questions are set out:

- How does innovation proceed within clusters?
- How does cluster strength affect innovation?
- How does globalization lead to stronger clusters?
- How do export and cluster strength correlate?

Two industries are chosen for applying the theory developed in the theoretical framework: the biopharmaceutical and the automotive industry. Pharmaceutical clusters are assumed to have strong innovative performance (See for example OECD, 2006). Further, the automotive clusters are assumed to have strong export performance (See for example Pezzini and Byrne, 2007). A dataset is used which contains data of European clusters for testing the hypotheses that correspond to the research questions. First a definition of clusters will be given, whereupon the outline of the thesis will be declared.

1.3 Research subject

There is not a well defined common definition of an industrial cluster. There is a difference in opinion in literature about how a cluster can be defined. That is why some definitions out of literature will be discussed and according to these insights a cluster definition for this research will be given. It is not a new observation that firms tend to co-locate in particular regions (see for example Smith, 1776, Marshall, 1890 and Von Thunen, 1826). Markusen (1996) explains the cluster concept as a specific location where firms may be drawn to, because of positive externalities. A well defined cluster definition of Porter is: "*a geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities"(Porter, 2003 p. 562).* As porter argues, a cluster consists of related industries because knowledge-spillovers should be the strongest in this case.[1] A more specific definition according to Cooke is: "*geographically proximate firms in vertical and horizontal relationships, involving a localized enterprise support infrastructure with a shared developmental vision for business growth, based on competition and co-operation in a specific market field… (Cooke, 2001 p.24)"* Despite this definition only clarifies the important role of interconnected firms, other important economic actors are also involved. As well as firms, public institutions have an important role in the dissemination of knowledge and innovation. Despite this, the European Commission measures cluster activity through employment rates and leaves public institutions out of the analysis, which makes it easy to point out clusters across Europe. Further, Porter and Cooke both state, geographic proximity is the most important feature of clusters since it elicits knowledge-spillovers and knowledge-flows among the economic actors.

Moreover, different cluster characteristics can be outlined. Ketels ascribes three characteristics to clusters (Ketels, 2004). In the first place, already argued above, proximity is an important feature. Firms accrue benefits because of the proximity to other firms. A high geographic proximity allows knowledge-spillovers and the sharing of common resources. In the second place, the economic actors within the cluster need to have a common goal. Just like Cooke (2001), Ketels emphasizes the shared developmental vision for business growth. In the third place, there are continuous amount of interactions between the economic actors. Benefits result from cooperation, new start ups, knowledge-spillovers and market relations. At last, a sufficient number of participants in the cluster must be active for having a meaningful impact on the cluster performance. A minimum amount of economic activity is needed to call it an industrial cluster. Given this last statement, it is important to notice that the

[1] Porter's view of clusters is supported by other authors. For example, Lindqvist (2009) distinguishes three industrial ranges, namely: single industries, general agglomerations which consist of all economic activity and clusters which (like Porter states) consists of related industries.

European Commission only recognizes districts as clusters if more than 1000 employees are involved (European Commission, 2007).

According to these insights a cluster definition which is supported by this research can be drawn: *A cluster is a district in which the employment rate of a specific industry is significantly higher than the employment rate represented on average in other surrounding regions. A high amount of diverse economic actors are involved (i.e. companies, universities and public organizations). Even more important are the linkages between the economic actors and the spillovers caused by these linkages.*

1.4 Outline project

The main content of this paper is organized as follows. Chapter two discusses the role of clusters policies, innovation and export. Within this chapter the theoretical framework is developed in which the research questions are addressed. According to this theoretical framework, hypotheses are derived. Chapter three describes the data and methodology which is used for testing the hypothesis. Next, in chapter four the empirical results are shown. These results are discussed in chapter five. Finally the main conclusion is drawn in chapter six.

2. Theoretical framework

This chapter describes the theoretical framework. The research questions, addressed in this paper, are being explained. Firstly, the theoretical framework is explained in paragraph 2.1. Paragraph 2.2 discusses how national and regional cluster policies are focused on strengthening European clusters. Secondly, paragraph 2.3 explains why stronger clusters have higher innovation rates. Paragraph 2.4 explains the relation of clusters and export. Finally, in paragraph 2.5 the automotive and pharmaceutical -industry are discussed.

2.1 Explaining the Theoretical Framework

Figure 1 Theoretical framework

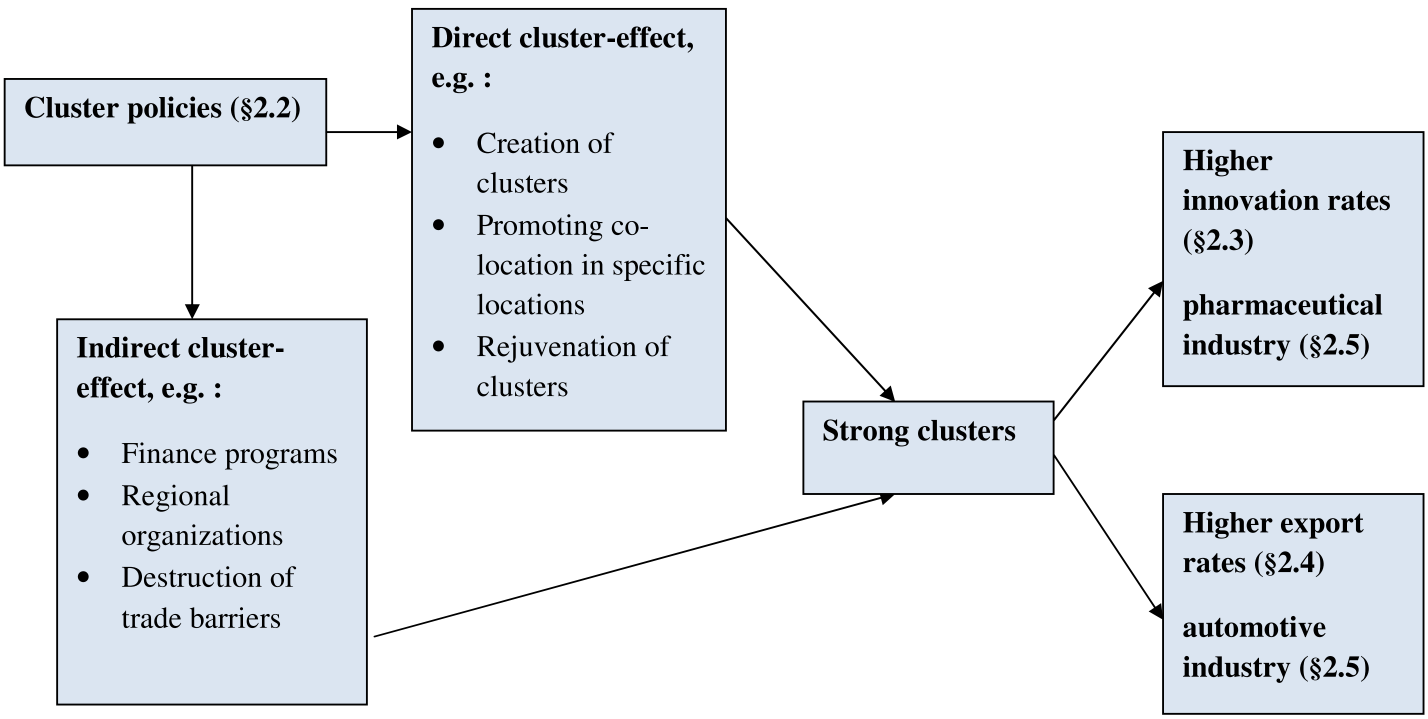


Figure 1 presents the theoretical framework of this chapter. In the first place it is important to understand why firms co-locate. Locating in clusters can be attractive because of the positive synergy effects of co-location. Geographic concentration of firms leads to productivity since cost advantages emerge from sources as climate, factors of production and infrastructure. In general, cost advantages explain about twenty percent of the variation in profits among industries (Madsen et al., 2004). Clusters allow companies to be more productive and innovative than they would be in isolation. Cooke (2001) explains different advantages arising from being co-located. In the first place, firms benefit from productivity gains. Lower transaction costs are involved as economic actors maintain trust based relationships. Besides this, firms gain from common purchasing, as this reduces transaction costs. In the second place, the presence of innovation-gains makes co-location more attractive. There is a pliant interaction between customer and supplier. An interactive process is physically easier and more effective, as a great part of intellectual knowledge cannot be codified. Another innovation gain is that qualified personnel can be recruited easier. In the third place, there are fewer barriers for new entrants, because information is locally available. For example, new ventures establish in clusters because of locally available inputs and skills.

Clusters emerge naturally or due to (direct and indirect) government policies (Nootenboom, 2008), see figure 1. Policies with direct or indirect effects on clusters will be defined in this research as *cluster policies*. Direct cluster policies are directly focused on some specific cluster (Solvell, 2003) For example, policymakers can focus on the creation of clusters, attraction of firms to some specific locations or the rejuvenation of declining clusters. These concepts will be explained in section 2.2.2. Indirect cluster policies are focused on other aspects, which on their turn can influence clusters. The cluster strength depends among others on the infrastructure of a country, the strength of competition, and the presence of high skilled workers (Wang, 2008). Indirect effects can be reached by, e.g. financial programs, regional organization and trade barriers. Indirect cluster policies give rise to stronger clusters, as economic actors are brought together and firms face no or less trade barriers. These concepts will be further explained in this chapter.

The motive for studying European clusters in this research is that the European Commission has stated in different reports that cluster strength will lead to higher export and innovation performance (see for example: European Commission, 2006b and European Commission, 2006a). This is why innovation (paragraph 2.3) and export (paragraph 2.4) are further explained in this theoretical framework. These concepts will be linked with cluster strength as it is suggested that stronger clusters will have higher export and innovation performance. Each of these concepts will be clarified by explaining the role of cluster strength and cluster performance for two specific industries. The pharmaceutical industry is used for explaining the connection of cluster strength with innovation, as it is expected that innovation and co-location are important in this industry (section 2.5.1). The automotive industry is used for explaining the connection of cluster strength with export, as it is expected that export and co-location are important in this industry (section 2.5.2).

2.2 National and regional cluster policies

In the last decade clusters have become a point to focus on for many policymakers. As mentioned in paragraph 2.1, one of the main targets of cluster policies is to spur both innovation and export (European Commission, 2006a). One of the reasons for the increasing focus on clusters is that companies are hampered to invest in Europe when there is not an innovation-friendly market (see section 2.3.1). Bottlenecks for investors are different levels of regulations and requirements across the member states, which raise the costs for investments. This is why a harmonized European policy is needed. How to create this innovation friendly market? Traditional messages from governments urging ventures to innovate are too simple. Filho (2004) argues that when firms are being encouraged to innovate, firms will do the opposite. Therefore an important indirect way to foster innovation and export is to encourage firms to co-locate by for example enhancing the conditions for technological development. European policymakers try to support national and regional policies by stimulating cluster growth. According to the European Commission (2007) cluster approaches, in which all the economic actors are involved are sufficient in creating the right environment for this specific growth. Solvell (2003) argues that policies can be directed at three levels: the cluster, the microeconomic environment and the general environment. In section 2.2.1 the different kind of cluster policy levels will be further explained. After this, in section 2.2.2, different policy targets will be discussed. Finally, in section 2.2.3 the conclusion will be drawn.

2.2.1 Cluster policy level

Cluster policies can be implemented on national, European and regional level. Following, all three will be discussed.

National policies are able to influence positively the economic infrastructure. Among others, a stable institutional environment makes it attractive for firms to co-locate. This requires competition laws and policies to be transparent and their implementation must be predictable. According to the Organization for Economic Co-operation and Development (2006b) transparency and predictability reduce the risk which is faced by investors. Unfortunately, systemic, market and government failures can make it less attractive for firms to co-locate[2]. The systemic institution is the combination of all mechanisms that create economic behavior and performance. There is a systemic failure when the combination of these mechanisms is being hampered (Woolthuis et al. 2005). By market institution is meant the price market system in which desirable activities are sustained and undesirable activities are prevented (Bator, 1958). National government can prevent systemic failures but according to Nootenboom (2008) it remains hard to prevent market failures. This is because a market failure is the result of structural rigidity. It is believed that government should compensate for market failures by taking a leading role (Krueger, 1990). Government failures occur when policies are unworkable. These failures can be opposed by implementing policies with a minimum of administrative and bureaucratic input (Krueger, 1990). Further, national policymakers can try to influence the economic performance by regulations. But to leave space for innovative solutions regulations should be focused on the political goal rather than on proposing technical solutions.

[2] Systemic failures are for example a lack of high skilled employees and inaccurate interests of economic agents. Market failures are for example the lack of sustainability and too strong competition. Government failures are for example a lack of local knowledge and the absence of a point of mutual interest

An important role of European policymakers is to monitor the cluster efforts of European countries (European Commission, 2008) Since industries often cross countries, an exclusive straight national policy will not be effective (Nootenboom, 2008). A European policy which overlooks a broader geographic area allows clusters to cross borders. Solvell et. al. (2003) argue that firms are shaped by the national business environment, as explained above, but that they are also linked to the global marketplace. Many firms obtain their materials and services by accessing larger markets. This is why Solvell et al (2003) state that less trade barriers and lower transportation costs will lead to more available global sources which will be used by firms for development and production.

Nonetheless, clusters appear because of the attractiveness of the region. This is why regional policies need to be implemented with regard to the unique local capabilities. Regional policy has a strong orientation on improving local competitive advantage and local production systems. During the post-war years regional policies were top-down national government models, providing infrastructures and financial support to firms. There is a general move towards a more bottom up (governance instead of government) approach, by focusing on supply side measures of technology development and transfer and by creating an enterprise culture. The present style of policy making is characterized by a prominent role of local organizations in shaping regional policy. Present policies also have a strong orientation on improving local competitive advantage and local production systems.

Lagendijk (1998) argues that the policy environment should be less hierarchical and more focused on network structures, in which all economic actors (public and private institutions) play crucial roles. It can be assumed that the European policy environment has no strong public authority, as all the actors in the private and public sector play important roles. Further, according to Lagendijk (1998), the most effective policy approach is to combine a bottom-up approach, with a monitoring top-down approach. This means that government should abstain from a continuous direct interference in specific clusters. Instead of this the government should be more focused on the infrastructure of a country and the circumstances which enhance the overall cluster strength. Government should merely focus on specific clusters if a direct cluster policy is needed. Just like Lagendijk (1998), Cooke (2001) supports the idea that government should only interfere when this is necessary for cluster development. Public intervention is important for enhancing development when there are already outsourcing firms or research laboratories seeking to commercialize knowledge (Cooke, 2001).

Often, clusters already exist. That is why public authority should discern the different stages of the cluster life cycle before implementing a cluster policy (Nootenboom, 2008). It is important to notice that although clusters pass through a number of stages, these stages may not always be identical. Despite this there is a general theory about the way clusters develop. Boschma (2007) discerns characteristic patterns by categorizing four stages of the lifecycle of a cluster. In short it will be discussed how the cluster lifecycle proceeds.

The first category is the introductory stage. During this stage clusters are assumed to emerge. A region already contains a number of firms and other economic actors. Some of the actors start to cooperate around the core activity by realizing common opportunities through their linkages (Andersson et al. 2004). Concerning firm characteristics the following is mentioned: there is high variety of firms, a limited amount of firms co-located and firms are depended on high tacit knowledge while they face a high uncertainty. During the second stage, the growth stage, the cluster is increasing in firms. During this stage new actors in related activities are attracted to the region. New linkages will appear. The network among the firms is growing towards a "core periphery". This is a network in which a core set of firms form a hub, while they are connected to others in the periphery (Anklam, 2007). The third category, the maturity stage, is characterized by a cluster size that is decreasing. This is the consequence of reaching a critical mass of actors. During this stage firms are more dependent on codified knowledge and face a low uncertainty. The network among the firms is growing toward a network "lock in". A lock in is the static dimension wherein firms do not learn, nor innovate (this concept is further explained in section 2.3.2). The fourth stage is characterized by a dissolving cluster and related networks. The cluster life cycle has to start over again to escape from disappearing.

Now will be explained how policies should change over the lifecycle of a cluster. According to Raines (2001) policy-making can be considered as a multi-stage process. This means that at every stage the policymakers can alter the policy goals and instruments. During the introductory stage an analysis should be made of the needs and the scope of the existing policy to address those needs. During the growth stage, it should be considered which clusters have the need of assistance. The main goal in the second stage is to energize business networks and halt market failures hindering development. During the third stage should be reconsidered if the available measures and regional policies address the problems and opportunities in this stage. New policy initiatives can be necessary to boost the cluster growth and prevent a lock-in effect. In the last stage the cluster had to adapt to market, technology and process changes in order to survive. This is why policymakers should be focused on the transformation of the disappearing cluster into new clusters. Often these new clusters are focused on other activities. According Andersson et al. (2004) policies during the cluster lifecycle ,may vary according to the national context. In some countries the public sector is more important than other economic actors during the early stages of the lifecycle, while in other countries the private sector plays the most important role from the start. These differences reflect the variation of responsibilities and competencies of public and private sectors across countries.

No matter on what kind of level (national, regional or European) policy is implemented: it still remains a tough issue for governments to create clusters. It can be assumed that the best thing policymakers can do is stimulating cluster growth by bringing economic actors together or stimulating co-location of firms. Policymakers can try to attract research branches to special zones, but synergy effects are hard to create. An important synergy effect is the interaction between the economic actors, as the network among the actors is the key of the cluster (Cooke, 2001). Often policymakers try to copy successful clusters from other places. However it seems almost impossible to create the same successful cluster, because different components and circumstances influence the performance of clusters. These circumstances cannot be simulated by government (Nootenboom, 2008). Two arguments can explain why cluster appearance is hard to influence (Brenner, 2004).

First of all, clusters seem to appear where there is a cost advantage. A cost advantage is hard to influence. It is possible to focus policy on decreasing transportation costs, in order to create a cost advantage. On the other hand the availability of natural recourses is rather complex to be influenced.

The second argument is related to the co-location of firms. It is hard to influence co-location given that firms often co-locate near customers, as there already has to be a located population or another industry. According to Lagendijk (1998) policymakers should recognize regional circumstances. If policymakers merely focus on emulating clusters from elsewhere, they do not understand the unique circumstances in which these clusters become successful (Lagendijk, 1998).

2.2.2Policy target

In this section different kind of policy targets aiming at creating stronger clusters are being discussed. Table 1 gives a literature overview of different policy targets on regional, national and European level.

Table 1 Cluster Policy focus on different policy levels

Cluster Policy level	**Policy target**	**Literature**
Regional Policy	• Boosting development in weak regions • Rejuvenation of declining clusters • Knowledge sharing	Solvell et al. (2003), Ketels (2004) Solvell et al. (2003) Box and Engelhard (2006)
National Policy	• FDI attraction • Creating an new venture culture	Solvell et al. (2003) Nootenboom (2008)

	• Creating an attractive institution and market environment • Finance programs • Support regional organizations	Wang (2008) European Commission (2006b), Box and Engelhard (2006) Lagendijk (1998), Storper (2000)
European Policy	• Destruct trade barriers • Harmonization of law among European countries	Storper (2000)

It is advocated in literature that cluster policies should not be focused at the creation, but at the development of clusters. Ketels (2004) argues that the activation of companies and institutions for jointly upgrading the cluster is more effective than merely investing in creating clusters without a fundamental reason. Although it is rather impossible to imitate clusters fundamentals of effective analysis do not differ. The explanation for this is that the awareness of cluster existence and a formalized membership-based association are the key to successful clustering (Cooke, 2001). When dialogues between purchasers and suppliers are stimulated and alternative ideas are encouraged, a more innovative environment could be created.

There are different initiatives that policymakers can take in order to stimulate clusters and to foster a more innovative culture. In the first place, policymakers can try to increase the number of firms in clusters. Important to notice is that new and small ventures are assumed to be more innovative than incumbents and larger firms. Start-ups are assumed to be more innovative than incumbents as the latter often try to postpone or halt new developments and inventions, since they experience damage as consequence of the loss of their attainment (Nootenboom, 2008). Smaller firms and new ventures can be more innovative because of different reasons. Smaller firms can easily adapt to consumer needs. Management of small firms is more in control and employees are more connected with the firm (Nootenboom, 2008). Nevertheless cluster policy should not merely be focused at new ventures and small enterprises. A low presence of large firms can limit the economic impact of clusters (European Commission, 2007). They are important as well, as they can afford R&D expenditures (Nootenboom, 2008). Nootenboom (2008) argues that incumbents possess more knowledge as they possess more experiences. Policy should be focused on Scooperation between smaller firms and larger firms as smaller firms other have a the lack of resources smaller.

In the second place, an important focus is an attractive environment for firms to innovate. Important are the market and institutional environment (Wang, 2008). Policymakers should shape a market environment in which development of goods and services are being encouraged. The market environment entails all the conditions outside the firm. To make the market environment more attractive, authority can focus on improving human resources. For example, students can be attracted to certain regions or sectors to be sure of a future skilled workforce.

The institutional environment is the system of formal laws, procedures, customs and norms, that restrain economic activity and behavior. A focus point regarding the institutional environment could be to improve the legal setting. Most important is that the institutional environment stimulates firms to innovate. Innovation can be promoted through enhancing cooperation between firms and public sector. Besides this, suppliers need the possibility to exploit their innovations in wider markets. To equalize this, there should be no static industrial standards, no entry barriers and protection of intellectual property.

The discussion above leads to the third argument that the government should destruct all barriers in the internal market. Otherwise mobility is hampered which hinders innovation. Examples of mobility, which fosters innovation, are highly skilled employees, venture capital, competition and investments. The promotion of export and internationalization encourages firms to interact (Nootenboom, 2008)

In the fourth place, through finance programs economic actors can be brought together. In this way venture capital and the finance of (joint) researches are being stimulated (European Commission, 2006b). Further, government should finance specific projects of small ventures as they often lack resources. An example is a tax reduction or subsidy for firms who invest in R&D.[3]

Another important focus for policymakers are regional organizations, which are amongst others: regional development agencies, government departments and business support and training agencies. According to the Commission, *"There is a very large community of "institutions", some of which may be associations or not-for-profit companies, whose task is to support innovation, particularly by SMEs*" (European Commission ,2006a p.18). These organizations are important because they are expected to be individually innovative and creative without any support. This is why they acquire more autonomy from central governments. These organizations base their policies on linkages they

---

[3] For Example: The Innovation Box in the Netherlands which leads to lower corporate tax for all the income of the firm which are covered by the Innovation Box. Instead of a corporate tax of 25.5%, firms pay 5%. (Article 12b *Wet op de Vennootschapsbelasting*)

have with other actors, through a "policy network". These policy networks play an important role in the exchange of knowledge, innovation and learning (Lagendijk, 1998).

Regional organizations are important for the cluster development, as these organizations bring different economic actors together and stimulate them to exchange knowledge. According to Storper regional organizations act "*as the transmission belts for moderately complex forms of knowledge* (Storper, 2000 p.31)". Face to face contact is often required inn order to facilitate the contacts among the different economic actors. Face to face contact is necessary when firms want to transfer tacit knowledge, as tacit knowledge is embodied in individuals and therefore hard to codify. It can be assumed that regional organizations contribute to the amount and strength of clusters in a certain region as they facilitate the (informal) contacts between firms and institutions. In summary, figure 2 shows several objectives and activities of cluster policies used by European regions and member states.

Figure 2 Objectives and activities of cluster policies

Objective

Activity	HR upgrading	Cluster expansion	Business development	Commercial collaboration	R&D and Innovation	Business environment
Information and contact brokerage	▪	▪▪▪	▪	▪▪▪	▪▪	
Practical assistance and advice	▪▪	▪▪▪	▪▪▪	▪	▪	
Direct financing and facilities	▪	▪▪▪	▪▪	▪	▪▪	
Events and training	▪▪▪	▪▪	▪	▪▪▪	▪▪	
Networking-Organising events	▪	▪	▪▪▪	▪▪▪	▪▪▪	▪▪
Lobbying						▪▪▪
Marketing	▪	▪▪			▪	▪
Monitoring and reporting	▪▪	▪▪▪	▪	▪	▪▪▪	▪▪▪

▪ ▪ ▪ Frequently used; ▪ ▪ Sometimes used; ▪ Occasionally used

Source: European Commission (2007), *Innovation clusters in Europe: A statistical analysis and overview of current policy support*, p 18. This figure presents an overview of current activities and the objectives of European member states, with regard to cluster development.

2.2.3 Conclusion

Because of the great diversity among the regions in Europe an exclusive European policy does not seem to be effective. National and regional policies are expected to seize possible failures on regional level since they have the capabilities to deal with the specific circumstances and characteristics of the region. Although cluster policies are not a panacea for taking away environmental weaknesses, it is suggested that an integrated national and regional cluster policy will be effective in enhancing cluster performance (see European Commission, 2007). As defended above in the literature discussion, one of the most important policy targets is regional organizations. These organizations foster interactions among all the economic actors and facilitate the flow of tacit knowledge. Cluster policies are assumed to foster innovation and export. In the next paragraphs the effect of clusters on innovation and export will be discussed.

2.3 Clusters and innovation

The following paragraph contains three sections. First an explanation is given on the role of innovation within clusters in section 2.3.1. Section 2.3.2 will focus on the important role of an interactive learning process. Further, geographic and cognitive proximity are discussed. Within section 2.3.3 a conclusion is given and a hypothesis will be set out.

2.3.1 Innovation in clusters

The last decade several initiatives have been taken to develop the European economy, as these are necessary as it seems that the growth of R&D investments has been stagnated since 2000 (Eurpean Commission, 2006a). An example of such initiatives is the report of the European Commission "Lisbon Strategy for Growth and Jobs", which is aimed at increasing R&D spending. The Commission reports that she wants to accomplish:*"..a truly knowledge-based and innovation-friendly society where innovation is not feared by the public but welcomed, is not hindered but encouraged, and where it is part of the core societal values and understood to work for the benefit of all its citizens*.(European Commission, 2006a, p. 1)" The report draws the conclusion that companies are being hampered to invest in Europe when there is not an innovation-friendly market. In an innovation- friendly market all economic actors like consumers, public agencies and companies are involved. Within this market supply of new ideas could push innovation while demand for new ideas could pull innovation. If consumers trust new products and services, new entrants could be less reluctant to enter the market with new ideas and innovations. Clusters seem to be the right means to foster this innovative culture. Motivations behind this will be explained further along.

According to Sollvell (2003) there are three important arguments as to why the innovation performance is higher within clusters. First of all, innovation brings high technical and economic uncertainty. For incremental problem solving, continuous interactions through networks and formal cooperation are needed.

Secondly, innovation takes place in a system of elements and links, through repeated interaction between economic actors. Within such a system feedback occurs between the creator and the applicator of innovative outcomes. That is because innovation is not a linear but a dynamic process (Nootenboom, 2008). The modern innovation-process defines innovation as non sequential interactions, different from the traditional model where innovation is just the outcome of a black box with an input (R&D) and an output (Innovation). Clusters are aligned with this modern innovation process (Ketels, 2004). Firms need to translate new information and create new ideas in order to innovate.

Thirdly, face to face contact is necessary for the exchange and creation of knowledge, which is easier to take place in high geographic proximity. Proximity is crucial in transferring tacit knowledge. The concept "tacit knowledge" will be further explained in section 2.3.2.

As clusters are aligned with the modern innovation process, innovation appears to be higher in clusters than outside of it. Innovation takes place through exploitation and exploration (Nooteboom, 2008). Exploitation is the application and improvement of ideas, while exploration is the occasion of new ideas. According to Gilbert and Kusar (2006) there is a strong relationship between co-locating and exploitative innovation. Exploitative innovation takes place as firms co-locate. Especially firms within the same sector or firms which are focused on similar target groups, will try to outperform their competitors (Gilbert and Kusar, 2006). Exploration often occurs at universities, research centers and R&D centers. Knowledge often spills over from universities and research centers to (new) ventures. (Monjon and Waelbroeck, 2003). Gilbert and Kusar (2006) support this strong relationship between knowledge-spillovers and explorative innovation. Figure 3 illustrates how exploration flows into exploitation and reverse.

Figure 3 Exploitation and exploration

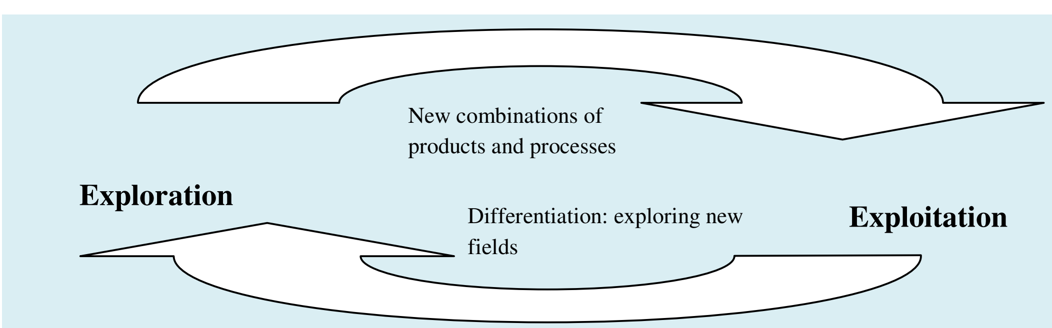


Figure 3 shows that a part of the inventions turns out in new combinations of technologies and products. After this an exploitation of some of the products or processes takes place. Existing knowledge can be applied to adapt and improve products. There is interaction between suppliers and consumers whereupon products and processes are improved. Eventually this results in the exploration of new products.

The framework in which all the economic actors interact while remaining their distinctive contributions, can be defined as an open innovation system. Since open innovation contains cooperation, entrance of outsiders within the cluster and relations with outsiders outside the cluster, clusters are drivers of open innovation (Nootenboom, 2008).

Thus, for firms to be innovative, location seems to matter. Firms within clusters are considered to perform well as they are driven by the cluster environment and spatially bounded knowledge dynamics (Boschma and ter Wal, 2007). A local concentrated market, such as a local labor market, contains a high mobility of resources. This allows people to flow from one situation to another and diffuse knowledge, which is a prerequisite for innovation. Clusters close the gap between the economic actors by bringing knowledge faster into the market, while giving the opportunity to form new linkages and apply new technologies.

2.3.2 Knowledge creation in clusters

Geographical proximity is a prerequisite for an interactive learning process among firms. The co-location of firms brings different synergy effects. Two important synergy effects are knowledge flows and knowledge spill-overs, which will be further explained.

In the first place, it is assumed that knowledge flows more often and easier between co-located firms. Knowledge-flows disperse knowledge and information. These flows contain the interactions among enterprises, universities and public research institutes. Both flows of knowledge and information seem to be the key to innovation (OECD, 1997). Boschma and ter Wal (2007) attribute four mechanisms which contribute to localized character of knowledge-flows.

The first mechanism is that knowledge is often dispersed by means of informal interaction. Through informal interactions, tacit knowledge is dispersed. Similar to codified knowledge, tacit knowledge plays an important role within an interactive learning process. Tacit knowledge is know-how, embedded in economic actors. This knowledge is geographically bounded in (high skilled) people, routines and machines (Phlippen and van der Knaap, 2007; Howells, 2002). Tacit knowledge must be communicated personally because it cannot be codified. That is why it is exchanged through informal interactions. In clusters tacit knowledge is transferred when economic actors meet face to face. Another way of transferring tacit knowledge is the mobility of scientists and qualified employees, as they are carriers of specified knowledge. Informal interaction makes expectations more predictable and reduces monitoring costs (Uzzi 1997). These interactions take place easier in geographic proximity because of lower transport and transaction costs.

The second mechanism is that knowledge streams through direct inter-firm linkages in cooperation networks. In literature it is argued that networks are often locally embedded (See for example Uzzi, 1997; Zukin and DiMaggio, 1990). Porter (2007) states that clusters contain strong networks of interrelated firms. This is because firms and institutions within a cluster form linkages more easily as they can form close and special relationships. Firms can benefit from trust based relations and high frequencies of interactions.

The third mechanism is that knowledge is transferred through labor mobility of (high skilled) employees between public and private organizations. Mobile labor often stays in the home region which makes it geographically localized (Breschi and Malerba, 2005).

The fourth mechanism is spin-offs. Knowledge is embedded in economic actors, such as employees. These employees disperse knowledge through spin-offs. Spin-offs often seem to be localized because they tend to establish in close proximity to the mother company (Tschang and Vang, 2008).

In the second place when firms co-locate they gain from knowledge-spillovers, which leads to productivity and innovation. This is because knowledge-spillovers provide important information about technology, competitors and market trends (Brown and Duguid, 2000). Spillovers can occur through horizontal relationships, e.g. between firms, and through vertical relationships, e.g. through buyer and supplier linkages (Madsen et al., 2004). Co-located Firms benefit from two kinds of knowledge-spillovers. Firstly, there are physical spillovers, which are directly visible externalities of co-location. Examples are the reduction in transportation costs and the possibility of specialization, as less specialized tasks can be outsourced in an easier way (Madsen et al., 2004). Secondly, there are intellectual spillovers. Intellectual spillovers contain the dispersion of codified knowledge. This is information codified in different sources, like publications and patents.

Despite the positive externalities of co-location, too little or too much of geographical proximity are unfavorable for learning and innovation. Too little proximity will lead to the absence of spatial externalities, like knowledge-spillovers. Too much proximity will lead to scarcity of openness, which eventually leads to a 'lock in effect' (Boschma, 2005). The lock in effect contains the static dimension where firms do not learn anymore from each other. This occurs when firms maintain long based relationships. At the long run a relationship can be unprofitable for the development of the firms, as they invest in the relationship, while there is no further progress. To prevent a lock in effect, relationships should be dynamic. To achieve dynamic relationships, outsiders have to enter the network and insiders have to retrieve (Nootenboom, 2008).

Similar to geographical proximity, other dimensions are seen as prerequisite for an interactive learning process between firms. An important dimension according to Boschma (2005) is cognitive proximity. Cognitive proximity is shaped by the constructive perspective and absorption capacity of firms. First of all, by a constructive perspective is meant an individual point of view. A point of view is being moderated by its perception, knowledge and morality. This will form a small or large cognitive distance between firms. Secondly, absorption capacity is the capacity to interpret perceptions, interpretations, conceptions and insights (Nootenboom, 2008). Both concepts will contribute to the capability to learn. The capability to learn is critical for the competitive advantage of firms and regions (Boschma, 2005). Companies can learn from each other as long as there is a variety between them (Nootenboom, 2008). That is why a problem arises when there is a small cognitive proximity, as companies possess different perceptions which make it hard to communicate. Differences in perception between companies arise due to boundary objects. This implies that for certain concepts specific interpretations or translations differ in different domains or countries (Lagendijk, 1998). That is why cognitive proximity is indirectly associated with geographic proximity, as the cognitive proximity seems to be higher when firms are co-located, e.g. firms share the same language and customs. Some distance on the other hand will facilitate a learning process between companies. That is why the optimal cognitive distance between firms has to be large enough to accommodate a learning process while firms have to possess similar absorption capacities (Nootenboom, 2008).

2.3.3 Conclusion and Hypothesis

Firms and public institutions can reach higher levels of innovation when they are co-located, as stated previously. One reason given for the stronger innovation within clusters is stronger competition. High levels of competition force firms to innovate in order to stay competitive in their geographic space (Gilbert and Kusar, 2006). Because of continuous interactions between the economic actors knowledge is dispersed. Knowledge-flows and knowledge-spillovers accelerate a learning process, which stimulates firms to innovate. Clusters give rise to new start-ups and business formations because the cost of failure is lower. For example, entrepreneurs can pull back in case of failure, as there are other local employment opportunities within the cluster (Oxford Research AS, 2008). The rise of new-startups is important because these ventures often possess new ideas (Gilbert and Kusar, 2006). Considering these assumptions it seems to be reasonable that stronger clusters will have higher innovation rates, which is also supported in literature (e.g. Porter, 2007 and Fagerberg et al, 2005). Different explanations can be put forward. As explained in the introduction, employment is a main variable for cluster strength. In the first place, there could be more knowledge-spillovers and knowledge-flows when a higher amount of economic actors are involved. In the second place the more economic actors are involved, the lower the probability of lock in effects. This is because firms can continuously refresh their inter-firm linkages as they are able to form new relationships and break up existing ones. Finally, firms have to innovate to stay competitive when there is more rivalry. This leads to the first hypothesis:

Hypothesis #1: Cluster strength has a positive influence on innovation performance.

2.4 Clusters and export

The following paragraph contains three sections. Section 2.4.1 explains the connection of clusters with globalization. Next, section 2.4.2, discussed the relationship between export and clusters. Finally, the conclusion and hypothesis are set out in section 2.4.3.

2.4.1 Globalization and local concentration

According to Porter (2007) globalization has made clusters more important. As Morrissey and Filatotchev (2001) argue, there are higher industrial export rates due to the lower transaction costs and less trade barriers. Globalization plays a key role in industries as it leads to competitive advantage in producing (parts of) products. As a matter of fact, international trade leads to stronger geographic concentration of firms, this is due to different reasons.

In the first place, globalization decreases trade barriers and transaction costs, leading to a geographical redistribution of economic activities. Redefined competitive advantages arise due to a shift to more specialized economies. Firms specialize in producing the products in which they have a competitive advantage and import the products in which they do not. Scale economies can now be realized and therefore stronger local concentration of activities occur (Storper, 2000).

In the second place, when a significant amount of trade barriers is reduced, more locations will be exposed to competition (Porter, 2007). It is said that this will lead to the survival of the fittest as clusters within ineffective locations will lose posture while stronger clusters will get stronger. Ketels supports this: *"When economic barriers fall, the overall number of clusters in a given field will fall as economic activity concentrates in the strongest locations. At the same time, lower trade barriers will increase the likelihood that strong clusters can outsource more standard activities such as manufacturing and concentrate on high-value functions in innovation (Ketels, 2004 p. 3)."*

In the third place, integration of Europe contributed to stronger concentration of economic activities. In the United States (US) there already exists an integrated market for decades. Due to this integration, clusters of the US appear to be world's strongest. According to Storper *"When referring to scale and comparative advantage effects on inter-industry trade, authors […] predict that the member countries of the European Union, as they pursue their project of integration, will become more similar to regions of the United States, which are much more sectorally-specialized than territories of similar extent in Europe (Storper, 2000 p.1)"*. Unfortunately, due to the high diversity among the European member states with regard to knowledge level and skills, it is conceivable that there will still be as many different locations as there are quality differences within an industry. However, it is also possible that lower income countries will benefit from open markets. These countries might enter a new market with a lower quality good, after which they upgrade this good as they obtain more skills from inter-industrial trade.

Nevertheless, it is been argued in that vanishing of trade barriers within Europe, does not necessarily lead to more geographic concentration. Storper (2000) argues that sectors in Europe are not becoming geographically concentrated in presence of rapidly increasing trade and disappearance of trade barriers. Instead of this, Geographical concentration will remain the same, as all firms extend their production instead of specializing. Knowledge about quality and productivity standards become well known internationally, since everyone can access this information due to the integration of markets. As a result firms will not specialize, but extend their production, which leads to a greater horizontally based competition. It is also argued that due to the integration of Europe, firms will mobilize themselves and generate differentiated products in different places, without being more specialized (Storper, 2000). However, with the fading of national borders firms will upgrade their knowledge and production. Given that globalization equalizes competitive advantages across Europe, clusters will get a more prominent role since firms will have to sustain a competitive advantage. Sustaining a competitive advantage can be achieved by co-locating, as for example firms become more depended on other firms and institutions.

2.4.2 Export and stronger clusters

Clusters seem to be strongest when companies face no, or low, barriers related to trade and investments (European Cluster Observatory, 2007). Industrial clusters can improve a country's export position (Porter, 1990). According to the Association of Governments (1999) 'export oriented' is one important feature common to all clusters. Between clusters and export exists a mutual causality (Karlsson et al., 2005). This mutual causality will be explained further in this section.

In the first place, co-location leads to more export. As explained in section 2.4.1, firms sustain a competitive advantage in producing (parts of) products. When a cluster gets more specialized (which indicates that the cluster becomes stronger), different components will be exported because all films engage in manufacturing their own components (United Nations, 2009). Firms co-locate in attractive locations, where they have access to unique recourses. The United Nations (2009) argues that co-location near raw materials leads to high export rates. This is because the co-location near raw material drives the export of these materials.

In the second place, a higher export level can lead to a stronger cluster. Several explanations can be put forward. In the first place, Ketels (2004) claims that the intensity of geographical concentration, due to industrial trade, depends on the characteristics of the industry. Concentration seems to increase in low growth industries, as firms in these industries restructure and focus on less production in fewer locations. Furthermore, concentration seems to decrease in high growth industries, as firms in these industries spread out into new locations with additional manufacturing activities.

In the second place, higher export levels lead to more employment. As explained in paragraph 2.3, the more economic actors involve, the stronger the cluster. The presence of exporting incumbents attracts other firms to co-locate. As explained in section 2.3.2, an important externality of co-location is the spillover of knowledge. Firms often establish near exporters, so they can benefit from export-spillovers and knowledge flows (United Nations, 2009). An Example of an export-spillover is the spillover of knowledge about foreign customers and foreign markets. Wiedersheim-Paul et. al. (1978) emphasize that exporting firms create positive attitudes towards non-exporting firms, especially when they are successively. Also Aitken et al. (1997) points out that export externalities drive co-location. According to him this is because export externalities, like export-spillovers, reduce the costs of access to foreign markets.

Export is an important performance measure for export industries (Christensen and Levinson, 2003). Export industries can be recognized by two characteristics. First of all, a significant share of production is being exported to customers outside the home region. Secondly, these industries are not depended on a specific location. This means these industries can be located anywhere, such that, they do not depend on local markets or natural resources. According to Christensen and Levinson (2003) export industries have better regional performance, like higher wages and stronger innovation levels. These industries achieve higher export rates if they co-locate, as export is their competitive advantage. The automotive industry is assumed to be an export industry with a strong local concentration in Europe (Pezzini and Byrne, 2007). There will be further elaborated upon this specific industry in paragraph 2.5.

2.4.3 Conclusion and Hypothesis

A redistribution of activities takes place, as a consequence of inter-industrial trade. Firms become more specialized and therefore co-locate in clusters. It is argued that European industries will get more geographical concentrated with the integration of the member states (see Storper, 2000). Globalization will foster cluster strength since more specialized economies will arise. This results in more export, as firms will focus on producing their own components. In the literature discussion above, different explanations are given for the positive influence of strong clusters on high export levels (see for example: Storper, 2000; Ketels, 2004; Porter, 1990). This leads to the second hypothesis:

Hypothesis #2: Cluster strength has a positive influence on export performance.

2.5 Pharmaceutical and automotive industry

This paragraph contains two sections. Section 2.5.1 discusses briefly the pharmaceutical industry wherein both the important role of innovation and related effectiveness of cluster policy will be touched upon. Section 2.5.2 looks at the automotive industry wherein the role of export and the related effectiveness of cluster policies will be discussed.

2.5.1 Pharmaceutical industry

It is augmented by Oxford Research AS (2008) that for national policies, clusters play the most important role for science, as almost half of the cluster programs are related to science and technology. First the important role of cluster policies in the pharmaceutical industry will be discussed. After this the important role of innovation within this particular industry will be elaborated upon.

In the first place, investment is one important key ingredient for pharmaceutical clusters (Audretsch, 2001). Two examples that show the important role of a cluster policy aimed at financing firms or bringing investors and firms together can illustrate this first statement. Firstly, public R&D investments in Sweden stimulated the emergence of strong clusters (Pezzini and Byrne, 2007). As a result Sweden contained high innovation rates and eventually a number of competitive innovations are generated.[4] The second example is one outside of Europe: the Sillicon Valley which is located in the U.S. A high amount of venture capital is invested in this region, which is one important reason why this cluster had the ability to grow that fast (Prevezer, 1997).

In the second place, policymakers play a crucial role in the construction of an effective institutional infrastructure. This infrastructure covers the degree of linkages between the innovation-related

[4] Innovations in Sweden are for example: pacemaker, gastric ulcer drugs, diagnostic allergy tests and equipment for protein separation (Pezzini and Byrne, 2007)

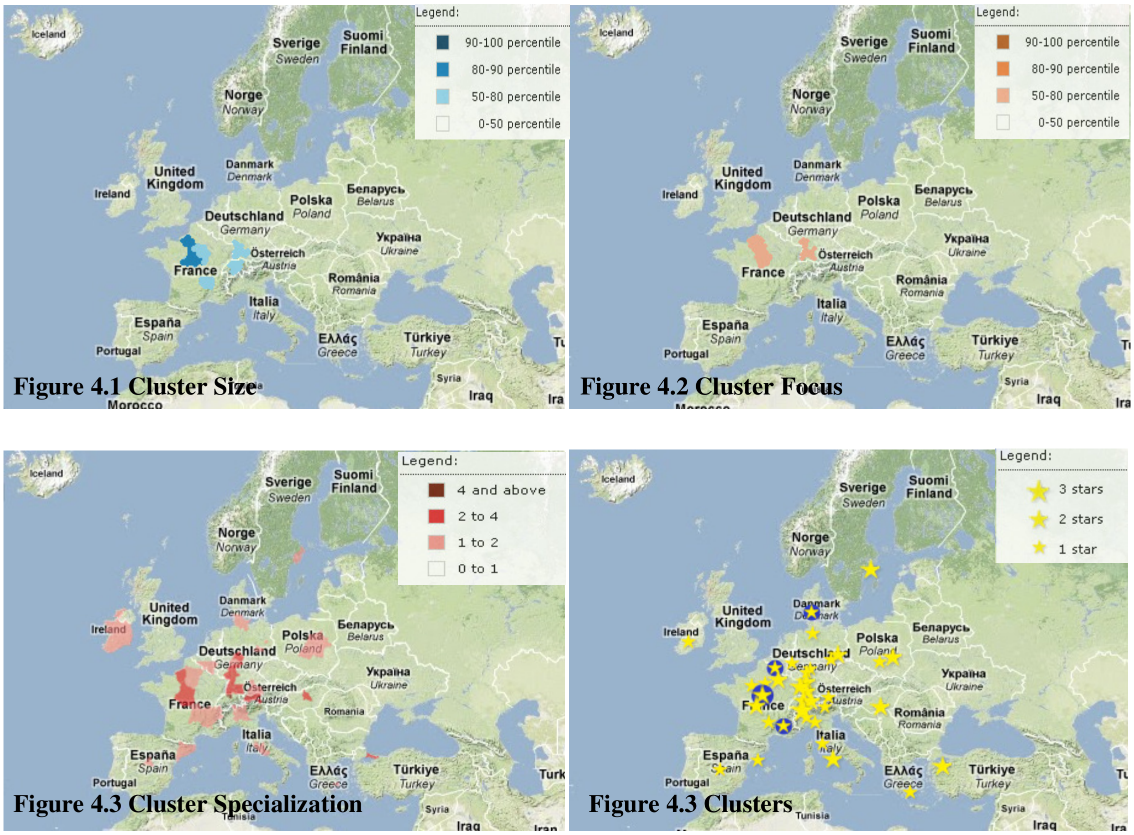
institutions and the private sector and the degree of networks (Ferranti et. al., 2003). Fan et. al. (2009) point out that the amount and the quality of a country's infrastructure affect the innovative performance of firms. OECD (2006) argues that the amount of interaction among companies is higher when there is a high amount of employees. Further, it is argued in literature that the presence of demand-side actors (like patent organizations); the characteristics of the public health-care systems (especially regulations) and regulations for new products have an important influence on the innovation process and size of the pharmaceutical market (OECD, 2006). Other important focus points in the institutional environment for the pharmaceutical industry according to Audretsch (2001) are the presence of large companies and an entrepreneurial culture. For example, in Sweden the presence of two major pharmaceutical firms drove the concentration of pharmaceutical companies (Pezzini and Byrne, 2007).[5]

Figure 4 illustrates the cluster indicators of the pharmaceutical industry. All the European pharmaceutical clusters are illustrated in the figure. As shown in figure 4, clusters are concentrated in Western Europe. Further, the figure shows that pharmaceutical clusters are strongest in France and Germany. Zucker et al. (1994) argue that most firms in pharmaceutical industry seem to co-locate near scientists. The pharmaceutical industry involves in design, discovery and development of new cures. This is why firms in this particular industry have a strong reliance on R&D. Firms in the pharmaceutical sector often collaborate in doing research, since the costs of drug development are too expensive for doing research themselves (especially for smaller firms, see for example: Cullen and Dibner, 1993). Box and Engelhard (2006) argue that partnership in this industry works best in proximity. The pharmaceutical sector is a knowledge-based industry as tacit knowledge and knowledge-spillovers play a crucial role (Busch, 2008). This is why geographic concentration is important for the maintenance of a competitive advantage. Given the important role in the pharmaceutical industry of clusters and innovation as a competitive advantage, the following hypothesis is stated:

Hypothesis #3: Pharmaceutical clusters have higher innovation performance than other industrial clusters.

[5] These firms are Astra and Pharmacia

Figure 4 Pharmaceutical clusters



Source: databank European cluster-observatory. Figure 4.1 presents the cluster size. Figure 4.2 presents the cluster focus. Figure 4.3 presents the cluster specialization. The stronger the color: the higher the cluster indicator. Figure 4.4 gives an overview of all the pharmaceutical European clusters, with minimal one star. Clusters are only recognized when they at least contain 1000 employees.

2.5.2 Automotive industry

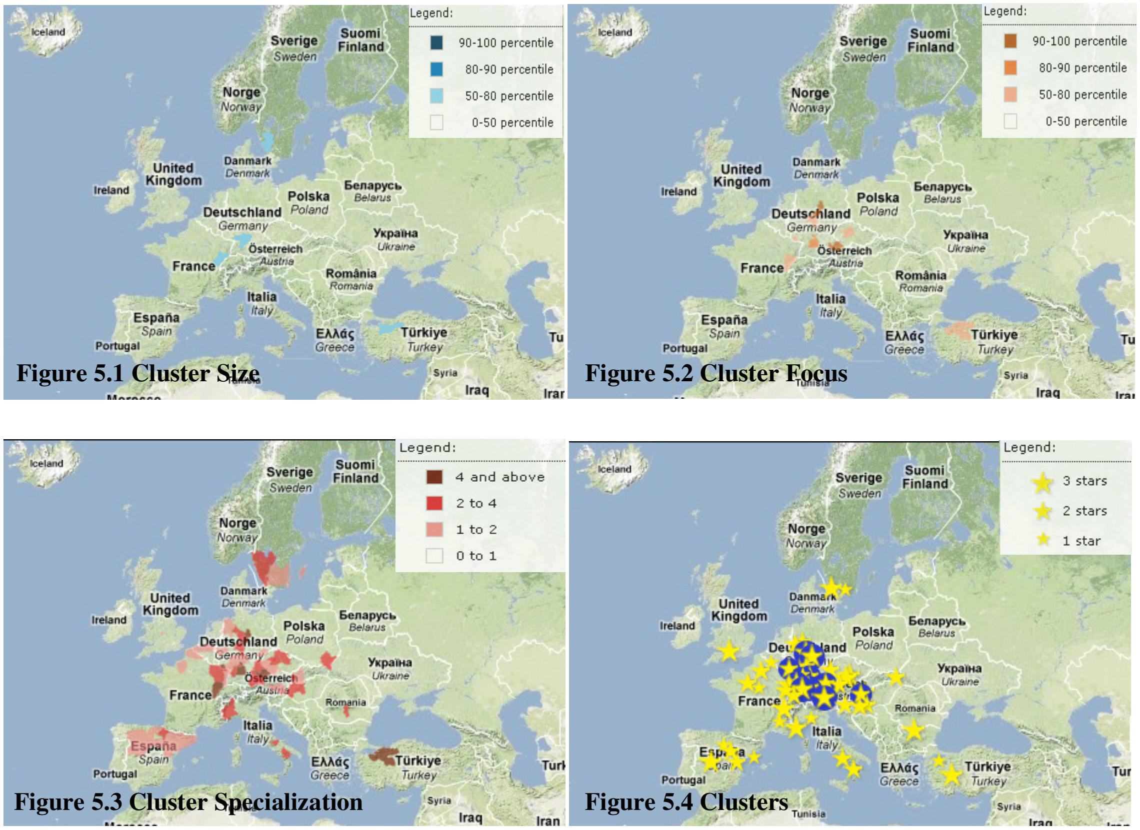
The automotive sector is an industry in which Europe shows a clear regional specialization (European Commission, 2007). More than fifty percent of all firms are located within regional clusters. Lecler (2002) states that car manufacturers and car parts-makers concentrate within clusters, instead of producing the same parts everywhere. As a consequence automotive clusters have high export rates. Reasons for co-location are political pressure, the need to collaborate with suppliers and customers and the attractiveness of locations with lower operation costs (Sturgeon et al., 2008). Clusters are specialized in designing and assembling automotive parts. Model specific parts seem to be produced close to final assembly plants to ensure delivery on time (See Lung et al., 2004 and Lecler, 2002). Because of lower labor costs and scale economies, non model specific automotive parts seem to be produced at geographic distance. This leads to higher export rates of these non model specific automotive parts. Firms tend to establish close to tuners which have led to some, so called, design centers[6], in which vehicle development is concentrated. Figure 5 presents the cluster indicators of the automotive sector and gives an overview of all the automotive clusters within Europe. Cluster in this industry seem to be strongest in Gemany and France as illustrated by figure 5.

Lagendijk (1998) argues that in the case of the automotive sector, top-down policy approaches can be effective. In top down approaches, policymakers target specific sectors. One important reason for implementation of cluster policies is that they create conditions for firms to co-locate. A non-European example of a successful cluster policy targeted at the automotive industry is the cluster policy in Thailand (Lecler, 2002). Within Thailand, during the 1990's, local requirements increased which required additional investments of car manufacturers. As a consequence of higher investment costs, the production of product-parts was outsourced and parts-makers opened new plants. These parts-makers tend to establish close to their customers and therefore industrial clusters arose. Government had to keep the institutional environment attractive, with regard to transport facilities, high skilled workers and tax exemptions. This national policy stimulated the cluster growth of the automotive industry.

Another example is the German automotive industry (Breschi and Malerba, 2005). In the 1990's the German government stimulated greater integration of innovation by means of subsidized projects. In this way suppliers learned to innovate by interaction. To prevent the risk of know-how streaming to competitors, public institutions guarded sensitive knowledge for innovation. The initiatives of policymakers leaded to more open innovation and competitive strength.

[6] Important design centers in Europe according to Sturgeon et al. (2008) are: Cologne (Germany), Russelsheim (Germany), Wolfsburg (Germany, Stuttgart (Germany) and Paris (France)

Figure 5 Automotive specialization and clusters



Source: databank European cluster-observatory. Figure 5.1 presents the cluster size. Figure 5.2 presents the cluster focus. Figure 5.3 presents the cluster specialization. The stronger the color: the higher the cluster indicator. Figure 5.4 gives an overview of all the automotive European clusters, with minimal one star. Clusters are only recognized when they at least contain 1000 employees.

Since the 1980s the automotive industry is growing towards an integrated global industry (Sturgeon et al., 2008). Globalization has attributed to stronger regional activities in the automotive sector (Lung et al., 2004). As a consequence, the Western European automotive industry has a strong export position (Becker, 2006). Firms are specialized in producing automotive parts or final assembly of it. Consequently these components are heavily traded. As export is a competitive advantage in the automotive sector and there is a strong co-location of automotive companies, the following hypothesis is stated:

Hypothesis #4: Automotive clusters have higher export performancs than other industrial clusters.

3. Data and Methodology

This chapter explains the data and methodology used in the research. Firstly, the source of the data used in this research is explained in paragraph 3.1. Secondly, the dataset which is constructed is explained in paragraph 3.2. Finally, the binary logistic regression and ordinal logistic regression analyses, which are applied in two different models, are explained in paragraph 3.3.

3.1 Data

A dataset is constructed to examine the influence of cluster strength on innovation and export. In section 3.1.1 the dataset will be discussed. Section 3.1.2 discusses the dependent variables. Section 3.1.3 discusses the independent variables. Finally, the control variables are discussed in section 3.1.4.

3.1.1 European Cluster Observatory

The analysis is based on data from the Cluster Mapping database, constructed by the European Cluster Observatory (ECO).[7] The Cluster Mapping database contains information about 259 European regions at NUTS 2 level[8] and 38 different industrial sectors, which will be further explained in 3.2.1. The information is collected by ECO through surveys and secondary data in 2007. First will be explained how ECO constructed the dataset, as the same data is used in this research.

Employment data

The Labour Force Survey and the Structural Business Statistics are used to collect employment data. An employment rate is declared for every industry at NUTS 2 level. Based on the employment data, ECO has constructed the cluster indicators, which will be explained on the end of this section.

Export and Innovation

ECO constructed two additional performance indicators in the dataset: innovation and export. The Regional Innovation Scoreboard (RIS) is used by ECO for constructing the innovation index.[9] As innovation is only measured at the regional level, regional innovation performance is assigned to the clusters within a specific region. Initially the value of ‘ innovation’ lied within an interval of 0 to 1. Either way ECO decided to rank this indicator on a 3 point scale, instead of using it as a scale variable.

[7] Data is collected from www.clusterobservatory.eu. ECO is managed by the Centre for Strategy and Competitiveness and financed through the INNOVA initiative by the European Commission’s DG Enterprise and Industry. ECO is founded to develop a web database and to collect data through surveys’ and other sources. The purpose of ECO is to inform policymakers and researchers about European clusters, cluster policies and cluster initiatives.

[8] All European member states are NUTS 1 regions. The NUTS 1 regions are subdivided in NUTS 2 regions. NUTS 2 regions are subdivided in NUTS 3 regions.

[9] RIS is conducted by Maastricht Economic and social Research and training centre for Innovation and Technology. The data is stemming from 2006.

The scale variable is translated into an ordinal variable by ECO to simplify the representation of RIS in their tables. So innovation performance is divided in three general categories: namely weak, medium and strong. Clusters with an innovation ratio of: 0 till 0,33 are ranked with 'low', 0,33 till 0,66 are ranked with 'medium' and 0,66 till 1 are ranked with 'strong'.

Export rates are collected by ECO from the International Cluster Competitiveness Project[10]. Export rates were available at NUTS 2 level per industry. The export indicator is assigned 'weak' if the export share in a given cluster is less than the export share of overall clusters. The ratio is calculated by dividing the export of the particular industry by the overall exports. If this ratio is in between 1 and 2, the export indicator is assigned with 'medium'. In case the ratio is higher than 2, the export indicator is assigned with 'strong'. So just like the innovation performance, the export performance is divided in three levels: weak, medium and strong. Both indicators, innovation and export, constructed by the ECO, are incorporated in this research.

Cluster Indicators

According to the ECO the development of spillovers and linkages depends on the cluster strength[11]. Cluster strength can be subdivided in three cluster indicators: cluster size, cluster specialization and cluster focus. The ECO appoints stars to clusters to indicate whether a cluster has reached a critical mass to develop positive spillovers and linkages. By measuring the three cluster indicators ECO demonstrates the extent to which clusters achieve the critical mass. All clusters are categorized by one, two or three stars. In case employment rate within a cluster is less than 1000 employees, the cluster receives zero stars, regardless of the cluster indicators. ECO only reported the clusters which reached the critical mass, as she wanted to prevent the appearance of very small insignificant clusters. This means that clusters with zero stars are left out of the dataset of ECO. As a consequence for this research zero star-clusters are also left out of the dataset, as complete information about these clusters is not available. These clusters are expected to have no meaningful economic effects and therefore have no value to the contribution of this research. This research is merely focused on the cluster performance of two and three star clusters compared with that of one star clusters. By comparing the performance of weak with strong clusters, conclusions can be drawn about the necessity for these weaker clusters to become stronger. So the definition of the critical mass which is formulated by ECO is also conducted in this research.

Now the cluster indicators which are formulated by ECO will be explained. The first cluster indicator is 'cluster size'. Employment rate is the main indicator for cluster size. Employment rates of all

[10] This is conducted by the Institute for Strategy and Competitiveness at Harvard Business School: http://data.isc.hbs.edu/iccp/index.jsp

[11] http://www.clusterobservatory.eu/index.php?id=49&nid=

clusters in Europe are listed by the ECO. The top ten percent of every European industrial sector receives one star. The second cluster indicator is 'cluster focus'. Cluster focus contains the extent to which the region is engaged upon production in the relevant industry. This indicator shows whether the cluster accounts for a larger employment share than the overall employment in the region it is located in. It is calculated by dividing the employment rate in the cluster by the total employment rate in the region. Figure 6 shows the formula for the calculation of cluster focus. The top ten percent of all clusters with the highest cluster focus indicator receive one star. The third cluster indicator is cluster specialization'. The specialization indicator illustrates the degree to which the cluster is specialized. The indicator shows whether the region is more specialized in a specific industry than the overall economy in Europe. The formula for the calculation of cluster specialization is illustrated in figure 7. Clusters with a specialization quotient of 2 or more receive a star.

Figure 6 Cluster focus

(Employment in the cluster) / (Total employment in the region)

Figure 7 Cluster specialization

$$\frac{\text{(Employment in the cluster) / (Total employment in the region)}}{\text{(Employment in the industry in Europe) / (Total employment in Europe)}}$$

3.2 Dataset

3.2.1 Dataset and variables

For this research, a database is constructed with information about 2109 different clusters across Europe. As explained above, data collected by ECO is used to construct the dataset for this research. Clusters are subdivided in 38 industries.[12] The data contains information about 31 European countries. Besides the EU-27 member states, four countries are included in the analysis, namely: Iceland, Norway, Switzerland and Turkey. To compare the amount of cluster-policies among European countries, additional variables are constructed and added to the dataset. In the first place the amount of clusters is mentioned for every European country. Table 1 and figure 1 in Appendix 1.1 show that

[12]These industries are: aerospace, analytical instruments, apparel, automotive, building fixtures, business services, chemical products, communications equipment, food, agricultural products, distribution services, education, entertainment, heavy machinery, financial services, fishing, footwear, forest products, furniture, heavy construction, tourism, information technology, jewell ery, leather, electrical equipment, construction materials, medical devices, metal manufacturing, oil and gas, biopharmaceutical, plastic, power generation and transmission, production technology, publishing and printing, sport, textiles, tobacco, transportation

Germany contains the most clusters rated by one, two and three stars. Italy and Poland belong to the top three of European countries with the most two star clusters. After Germany: Romania and Turkey contain the most three star clusters. When the percentage of two and three star clusters out of total clusters is taken into account, Malta, Romania and Lithuania seem to have more two and three star cluster than one star clusters (Figure 2, Appendix 1.2). It is important to notice that Malta and Lithuania only contain a small amount of total clusters in comparison with the other European countries. Germany still has a high percentage of two and three stars clusters (38,2%). Table 2 in Appendix 1.3 illustrates the amount of cluster policies and organizations in the European countries. The table shows that when more cluster policies are implemented, a country contains more clusters. A great part of the countries, which have implemented no or only a few cluster policies, still have a high percentage two and three clusters (see for example Czech Republic and Ireland).

The analysis contains four dependent variables, used in eight different models, and thirty-nine independent variables of which thirty-one are control variables, namely country dummies. Appendix 2 gives an overview of the variables used in the model. The variables will be explained in the following sections.

3.2.2 Dependent variables

To measure whether cluster strength influences export and innovation, four dependent variables are used in eight different models (the models are explained in section 3.3.1). The first variable is the ordinal variable 'Innovation". This variable is coded 1 for weak innovation, 2 for normal innovation and 3 for strong innovation. Section 3.1.1 explains how the variable is created.

The second variable is the ordinal variable 'export'. This variable is coded 1 for weak export, 2 for normal export and 3 for strong export. Section 3.1.1 explains how the variable is created.

Further, both ordinal variable explained above are transformed in dichotomous variables. The third variable is the dummy variable 'InnDummy'. The dummy is coded '1' if innovation is high or medium and '0' if innovation is low.

The fourth variable is 'ExDummy'. The dummy is coded '1' if export is high or medium and '0' if export is low.

3.2.3 Independent variables

Five independent main variables are used in the analyses. The first, second and third independent variable are used as a proxy for cluster strength. All clusters in the dataset are ranked by stars. Subsequently, an ordinal variable for cluster strength is created: coded as one, two or three stars.

Further, dummy variables are added to the model. If the conducted analysis shows a difference between the observed value and the true value, this difference might be attributed to heterogeneity, as individual variables might differ. To control for heterogeneity, dummy variables are created.

To measure the effect of cluster strength on innovation and export, the ordinal variable for cluster strength is transformed into three cluster dummies. The cluster dummies are: 'OneStarDummy', TwoStarDummy' and 'ThreeStarDummy'. 'OneStarDummy' is used as a reference in the model.

Three cluster-indicators: 'size', 'focus' and 'specialization' are used in the model, which are scale variables. Adding these cluster-indicators to the model provides a better understanding about the relationship between cluster strength and de dependent variables. These scale variables are log-transformed.

Furthermore, dummies are created of industries to control for heterogeneity as cluster performance might differ across industries. 'Dummy1' is added to the model. 'Dummy1'is coded '1'if the cluster is an automotive cluster and coded '0' for all other industrial clusters. 'Dummy2' is added to the model. 'Dummy2' is coded '1' if the cluster is a pharmaceutical cluster and coded '0' for all other industrial clusters.

3.1.4 Control variables

In addition to the independent main variables, thirty-one control variables are used in the analyses. Country dummies are added to the model. These dummies are used to control for heterogeneity as cluster performance might differ across countries. Dummies are made of EU-27 member states, Iceland, Norway, Switzerland and Turkey.

With respect to innovation, Countries in Eastern Europe are expected to have lower innovation performance. New ideas, technologies and standards are introduced in Eastern Europe through foreign direct investments (Dawn & Nigel, 1998). Anyway, it is expected that Eastern Europe is less innovative than other parts of Europe. Despite the recovery of the post socialist countries, it is argued in literature that there is not a recovery in demand for technology and R&D investments. Filho (2004) points out that those countries in Eastern Europe struggle to maintain strong patterns of innovative activity, as a cause for the lack of information recourses and their unbalance of political and economic power. Radosevic (2004) argues that Eastern Europe faces a gap between local demand and supply for R&D and innovation. Further, with respect to export, Countries in Eastern Europe are expected to have lower export performance as well. Table 2 illustrates the amount of export in 2008 in Europe. As illustrated in the table, Countries in Eastern Europe have the lowest export rate in 2008 (respectively 4 % of the total export in Europe).

Table 2 Export-rates across Europe

	Export (x Million)	Share %
Western-EU	52,505	67
Northern-EU	14,036	18
Southern-EU	8,929	11
Eastern-EU	2,862	4

Source: Data is derived from www.eurostat.nl. It contains export data of the EU-27 stemming from January 2008 till December 2008. Export rates of Norway, Turkey, Switzerland and Iceland are not taken into account.
Northern- Europe: Denmark, Estonia, Finland, Ireland, Latvia, Lithuania, Sweden, United Kingdom *Western- Europe*: Netherlands, Belgium, Luxembourg, France, Austria, Germany, *Eastern- Europe:* Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, *Southern-Europe*: Cyprus, Italy, Malta, Portugal, Macedonia, Slovenia, Spain, Greece

3.2 Methodology

3.2.1 Eight models

Eight models have been constructed in order to test for the effect of cluster strength on performance of export and innovation. Similar independent variables are used in all models. In the first place to control for cluster strength, the star dummies and cluster indicators are added to the models. As explained in paragraph 2.4 the pharmaceutical industry is expected to be positively correlated with innovation while the automotive industry is expected to be positively correlated with export. Finally, 'Country dummies' are added to the models to control for differences in cluster performance across Europe. The dependent variable 'innovation' is used in the first, second, third and fourth model and the dependent variable 'export' is used in the fifth, sixth, seventh and eighth model. Figure 8 illustrates the models.

Figure 8 Models

Model 1 Binary Logistic Regression

Independent Variables: 1 star Dummy
2 star Dummy
3 star Dummy

Pharmaceutical Dummy
Automotive Dummy

Control Variables: Country dummies

Dependent Variable:
Innovation Dummy

*The econometric equation can be written as:

$$\text{Ln}\,(y/1\text{-}y)= \beta_0 + \beta_1\,(\text{1starDummy}) + \beta_2\,(\text{2starDummy}) + \beta_3\,(\text{3starDummy}) + \beta_4\,(\text{AutomotiveDummy}) + \beta_5\,(\text{PharmaDummy}) + \beta_6(\text{Netherlands}) + \ldots + \beta_{37}(\text{Germany})$$ [13]

Model 2 Binary Logistic Regression

Independent Variables: Cluster Size
Cluster Specialization
Cluster Focus

Pharmaceutical Dummy
Automotive Dummy

Control Variables: Country dummies

Dependent Variable:
Innovation Dummy

*The econometric equation can be written as:

$$\text{Ln}\,(y/1\text{-}y)= \beta_0 + \beta_1\,(\text{Size}) + \beta_2\,(\text{Focus}) + \beta_3\,(\text{Specialization}) + \beta_4\,(\text{AutomotiveDummy}) + \beta_5\,(\text{PharmaDummy}) + + \beta_6\,(\text{Netherlands}) + \ldots + \beta_{37}(\text{Germany})$$ [14]

[13] Added to the model: All 27 EU countries, Iceland, Norway, Switzerland and Turkey

[14] Added to the model: All 27 EU countries, Iceland, Norway, Switzerland and Turkey

Model 3 Ordinal Logistic Regression

Independent Variables: 1 star Dummy
2 star Dummy
3 star Dummy

Pharmaceutical Dummy
Automotive Dummy

Dependent Variable:
Innovation Ordinal

Control Variables: Country dummies

*The econometric equation can be written as:

$$\text{Link }(y)= \theta\text{-}(\ \beta_1\ (\text{1starDummy}) + \beta_2\ (\text{2starDummy}) + \beta_3\ (\text{3starDummy}) + \beta_4\ (\text{AutomotiveDummy}) + \beta_5\ (\text{PharmaDummy}) + \beta_6 (\text{Netherlands}) + \ldots + \beta_{37} (\text{Germany})^{15})$$

Model 4 Ordinal Logistic Regression

Independent Variables: Cluster Size
Cluster Specialization
Cluster Focus

Pharmaceutical Dummy
Automotive Dummy

Dependent Variable:
Innovation Ordinal

Control Variables: Country Dummies

*The econometric equation can be written as:

$$\text{Link }(y)= \theta\text{-}(\ \beta_1\ (\text{Size}) + \beta_2\ (\text{Focus}) + \beta_3\ (\text{Specialization}) + \beta_4\ (\text{AutomotiveDummy}) + \beta_5\ (\text{PharmaDummy}) + + \beta_6\ (\text{Netherlands}) + \ldots + \beta_{37} (\text{Germany})^{16}\ )$$

[15] Added to the model: All 27 EU countries, Iceland, Norway, Switzerland and Turkey

[16] Added to the model: All 27 EU countries, Iceland, Norway, Switzerland and Turkey

Model 5 Binary Logistic Regression

Independent Variables: 1 star Dummy
2 star Dummy
3 star Dummy

Pharmaceutical Dummy
Automotive Dummy

Dependent Variable:
Export Dummy

Control Variables: Country Dummies

*The econometric equation can be written as:

$$\text{Ln }(y/1\text{-}y) = \beta_0 + \beta_1\,(\text{1starDummy}) + \beta_2\,(\text{2starDummy}) + \beta_3\,(\text{3starDummy}) + \beta_4\,(\text{AutomotiveDummy}) + \beta_5\,(\text{PharmaDummy}) + \beta_6(\text{Netherlands}) + \ldots + \beta_{37}(\text{Germany})$$[17]

Model 6 Binary Logistic Regression

Independent Variables: Cluster Size
Cluster Specialization
Cluster Focus

Pharmaceutical Dummy
Automotive Dummy

Dependent Variable:
Export Dummy

Control Variables: Country Dummies

*The econometric equation can be written as:

$$\text{Ln }(y/1\text{-}y) = \beta_0 + \beta_1\,(\text{Size}) + \beta_2\,(\text{Focus}) + \beta_3\,(\text{Specialization}) + \beta_4\,(\text{AutomotiveDummy}) + \beta_5\,(\text{PharmaDummy}) + + \beta_6\,(\text{Netherlands}) + \ldots + \beta_{37}(\text{Germany})$$[18]

[17] Added to the model: All 27 EU countries, Iceland, Norway, Switzerland and Turkey

[18] Added to the model: All 27 EU countries, Iceland, Norway, Switzerland and Turkey

Model 7 Ordinal Logistic Regression

Independent Variables: 1 star Dummy
2 star Dummy
3 star Dummy

Pharmaceutical Dummy
Automotive Dummy

Control Variables: Country Dummies

Dependent Variable:
Export Ordinal

The econometric equation can be written as:

Link (y)= θ-(β_1 (1starDummy) + β_2 (2starDummy) + β_3 (3starDummy) + β_4 (AutomotiveDummy) + β_5 (PharmaDummy)+ β_6(Netherlands)+...+ β_{37}(Germany)[19])

Model 8 Ordinal Logistic Regression

Independent Variables: Cluster Size
Cluster Specialization
Cluster Focus

Pharmaceutical Dummy
Automotive Dummy

Control Variables: Country Dummies

Dependent Variable:
Export Ordinal

*The econometric equation can be written as:

Link (y)= θ-(β_1 (Size) + β_2 (Focus)+ β_3 (Specialization)+ β_4 (AutomotiveDummy) + β_5 (PharmaDummy)+ + β_6 (Netherlands)+...+ β_{37}(Germany)[20])

3.2.2 Binary Logistic and Ordinal Logistic Regression

A binary logistic regression and ordinal logistic regression are used to test the hypotheses formulated in the literature part. In this section will be discussed why binary logistic regression and ordinal logistic regression are most suitable for accomplishing the analysis. These regression analyses are used instead of using the ordinary least squares (OLS), as the assumptions of the OLS regression are not met.

[19] Added to the model: All 27 EU countries, Iceland, Norway, Switzerland and Turkey

[20] Added to the model: All 27 EU countries, Iceland, Norway, Switzerland and Turkey

Unlike OLS regression, logistic regression does not assume linearity of relationship between the independent en dependent variables, although it requires that the independent variables are linearly related to the logit of the dependent.

Further, a logistic regression does not require normally distributed variables. Dichotomous dependent variables are used in 4 models. The predicted values in the models are probabilities of a high and medium innovation and export level. As the probability of the outcome lies between 0 and 1, using the binary logistic regression is more practical than using the OLS regression, as the latter allows the dependent variable to take greater values than 1, and/or lower values than 0 (Pampel, 2000). This is why the ordinal variables 'innovation' and 'export' are converted into dummies, after which a binary logistic regression is used to test the hypotheses.

A logistic regression neither assumes homoscedasticity. All models contain dichotomous dependent and independent variables. Besides the dummies, three independent scale variables (cluster indicators) are used. Cohen (2003) argues that in case the dependent variables are not scale variables, the application of an OLS regression will result in heteroscedasticity. Ordinal dependent variables are used in 4 models. McCullagh and Nelder (1989) created a model, in which the response variable is ordinal. They showed how important it is to specify whether there is a skewed or symmetric linkage; otherwise this can lead to a poor prediction. This is why an ordinal logistic regression analysis is used to test the ordinal variables, as one or more assumptions will be violated when ordinal variables are treated as scale variables.

3.2.3 Multicollinearity

There should not be a strong correlation among the independent variables. The outcome will be biased if correlations among independent variables are too strong, due to the fact that the effect of strongly correlated independent variables is hard to specify. Menard (2002) points out that information for multicollinearity can be obtained by using an OLS model, by which one has to test whether the independent variables are correlated. Most results can be ignored in the OLS output. Only the variance inflation factor (VIF) is useful, as this indicator controls for multicollinearity. The VIF should be at most five. Therefore the OLS model is used to control for multicollinearity. The results of the test are displayed in Appendix 3. Table 2 of appendix 3 shows there is no significant relationship among the independent variables, as all values of the VIF are below five.

Besides the disadvantages explained in the previous section, a disadvantage of using the OLS regression for testing multicollinearity is that it assumes that the model contains continuous dependent variables. As for the greater part dichotomous variables are used in the models, the utility of the outcome of using the OLS model declines. This is why the correlation is also tested with the Correlation Matrix. The Correlation Matrix can be used to test the correlation of categorical data

(Keller, 2008). Higher Correlations than 0.7 are considered as strong. The outcome of the test is illustrated in the table 1 in Appendix 3. The results of table 1 show that there is no strong correlation between the independent variables in the model.

3.2.4 R-Square

It is not possible to compute the R-Square with the characteristics of the OLS model when the binary logistic regression is used. Therefore other methods are used to estimate the coefficient of determination. Cox and Snell's R-Square is based on the log likelihood for the model, compared to the log likelihood for a baseline model. This is not a perfect way of estimating the coefficient as it always has a maximum value less than 1 if dichotomous variables are used in the model. Instead of Cox and Snells R-Square, the Nagelkerke's R-Square can have a minimum value of 0 and a maximum value of 1 if dichotomous variables are used in the model. This is why the results in chapter 4 illustrate both R-Squares to show the degree in which the variation of the dependent variable can be explained by the independent variables.

4. Empirical results

This chapter describes the results of the analysis used to test the hypotheses. The Binary Logistic Regression is executed with SPSS. Paragraph 4.1 discusses the results of the first, second, third and fourth model. Paragraph 4.2 discusses the results of the fifth, sixth, seventh and eighth model.

4.1 Results Model 1&2

A binary logistic regression is used to test the variables in model 1 and 2. Two models are created as the variables cluster indicators and cluster stars are related with each other. In both models innovation is used as dependent variable. In the first model cluster dummies for stars are used as independent variables while in the second model cluster indicators are used as independent variables. Appendix 4 illustrates the analysis of the first model. Appendix 5 illustrates the analysis of the second model. Both models show different results as the independent variables used in the models differ. Further control variables are taken into account in both models, namely European country dummies. The results of the models are illustrated in table 3. The results of model1 are illustrated on the left and the results of model 2 are illustrated on the right.

Table 3 Model 1&2:Binary Logistic Regression

Number of Observations		1675		1674
R-Square				
Cox and Snell		0.406		0.464
Nagelkerke		0.577		0.658
	ß	S.E.	ß	S.E.
Cluster Strength				
Size			**1.460	0.139
Specialisation			**-1.456	0.179
Focus			0.109	0.090
TwoStarDummy	0.235	0.337		
ThreeStarDummy	0.129	0.174		
Industries				
Automotive	0.202	0.452	0.647	0.511
Pharmaceutical	*2.064	0.903	1.624	0.898
Constant	-0.864	0.260	-0.840	0.305

Note: (*) means significant at 5% level, (**) means significant at 1% level
dependent variable is: MedHighInnDummy: (1)= Medium and High Innovation
Controlled for country fixed effects (country dummies): yes

4.1.1 R-Square

The R-Square of model 1 is illustrated in Appendix 4. Cox and Snell's R-Square is 0.406. Nagelkerke's R-Square is 0.577. Therefore 57% of the variation in the dependent variable 'innovation' is explained by the independent variables in model 1. The R-Square of model 2 is illustrated in Appendix 5. Cox and Snell's R-Square is 0.464. Nagelkerke's R-Square is 0.658. Therefore 66% of the variation in the dependent variable 'innovation' is explained by the independent variables in model 2.

4.1.2 Cluster Strength

Cluster size has a positive ß-coefficient of 1.460 and a standard error of 0.139. The first cluster indicator shows a significant result. The exp(ß) (exp(1.460)) of Cluster Size is 4.307. For every increase in cluster size, it is 4.307 times more likely that this cluster has a medium or high innovation performance. This indicates an increasing value of cluster size ratio will increase to probability of a higher level of innovation. Cluster specialization has a negative ß-coefficient of -1.456 and a standard error of 0.179. Also the second cluster indicator shows a significant result. The exp(ß) of cluster specialization is 0.233. This means that for every increase in cluster specialization it becomes less likely that the cluster has a high or medium innovation performance. It can be assumed that a decreasing value of cluster specialization increases the probability of a higher innovation performance. Cluster focus has a negative ß-coefficient of 0.109 and a standard error of 0.090. This indicator does not show any significant result.

However, when the cluster stars are taken into account, there is no significant relationship between stars and innovation. The dummy 'one star' is used as a reference in the model. The results show that there is no positive or negative significant difference between strong clusters (two and three star clusters) and one star clusters with regard to innovation. Nevertheless, the dummies both have a positive ß-coefficient. Although the difference between two and one star clusters is not significant, the results do indicate that two and three star clusters have higher innovation rates than one star clusters.

4.1.3 Industries

The results in both models show that the automotive industry (Dummy 1) does not have significant higher or lower innovation rates than other industries in the model. Further, in the first model the pharmaceutical industry (Dummy 2) has a significantly higher innovation performance than other industries in the model. the ß-coefficient is 2.064. The Exp(ß) of the pharmaceutical industry is 7.878. This means that clusters related to the pharmaceutical industry are 7.878 times more likely to have a medium and high innovation performance than other industrial clusters in the model.

4.2 Results model 3&4

An ordinal logistic regression is used to test the variables in model 3 and 4. The dependent variable innovation, which used in both models, is an ordinal variable. Cluster stars are used as independent variables in the third model. Appendix 6 illustrates the outcome of the analysis of model 3. In the fourth model cluster indicators are used as independent variables. Appendix 7 illustrated the outcome of the analysis. Further European country dummies are used as control variables in both models. In The outcomes of both analyses are illustrated in table 4. Model 3 is illustrated on the left and model 4 is illustrated on the right.

Table 4 Model 3&4: Ordinal Logistic Regression

	Estimate	S.E.	Estimate	S.E.
Cluster Strength				
Size			**0.478	0.049
Specialisation			**-0.140	0.020
Focus			-0.024	0.018
TwoStars	*0.186	0.150		
ThreeStars	*0.320	0.078		
Industries				
Automotive	0.097	0.212	0.287	0.213
Pharmaceutical	0.483	0.290	0.296	0.288

Note: (*) means significant at 5% level, (**) means significant at 1% level
dependent variable is: Innovation: (1)= low (2)=medium (3)=high
Controlled for country fixed effects (country dummies): yes

The results of table 4 correspond to the results of table 3. Model 4 and model 2 both show significant relationships at 1% level between innovation and cluster indicators. In both models cluster size is positively related to innovation. Also specialization shows a significant negative relationship in both models. An increasing value of cluster size will corresponds to an increasing probability of being in one of the higher outcome categories of innovation performance, as the coefficient of cluster size is positive (0.478). On the opposite, an increasing value of cluster specialization corresponds to an increasing probability of beoing in one of the lower outcome categories of innovation performance, as the coefficient of cluster specialization is negative (-0.140).

Although two stars and three stars dummies in model 1 did not show any significant result, model 3 shows a significant relationship between cluster stars and innovation. Both dummies are positively related to innovation. One star dummies are left out of the analysis, as they are used as a reference. The coefficient of two star dummies is 0.186 and for three star dummies 0.320. This means that clusters with two and three stars are more likely to be in the higher outcome categories of innovation performance than those with one star.

Model 2, 3 and 4 did not show any significant result regarding to industry dummies. Only model 1 showed a significant relationship between pharmaceutical industry and innovation performance.

4.3 Results Model 5&6

A binary logistic regression is used to test the variables in model 5 and 6. The dependent variable in both models is export. In the fifth model cluster dummies for stars are used as independent variables while in the second model cluster indicators are used as independent variables. Appendix 8 illustrates the analysis of the fifth model. Appendix 9 illustrates the analysis of the sixth model. Further control variables are taken into account in both models, namely European country dummies. The results of the models are illustrated in table 3. The results of model 5 are illustrated on the left and the results of model 6 are illustrated on the right.

Table 5 Model 5&6: Binary Logistic Regression

Number of Observations		1795		1794
R-Square				
Cox and Snell		0.096		0.109
Nagelkerke		0.130		0.148
	ß	S.E.	ß	S.E.
Cluster Strength				
Size			0.002	0.078
Specialisation			**0.648	0.110
Focus			**0.221	0.059
TwoStarDummy	**1.188	0.232		
ThreeStarDummy	**0.486	0.118		
Industries				
Automotive	**1.333	0.453	**1.317	0.452
Pharmaceutical	**1.310	0.463	**1.286	0.465
Constant	0.879	0.294	0.512	0.308

Note: (*) means significant at 5% level, (**) means significant at 1% level
dependent variable is: MedHighExpDummy: (1)= Medium and High Export
Controlled for country fixed effects (country dummies): yes

4.3.1 R-Square

The R-Square of model 5 is illustrated in Appendix 8. Cox and Snell's R-Square is 0.096. Nagelkerke's R-Square is 0.130. Therefore only 13% of the variation in the dependent variable 'export' is explained by the independent variables in model 5. The R-Square of model 6 is illustrated in Appendix 9. Cox and Snell's R-Square is 0.109. Nagelkerke's R-Square is 0.148. Therefore only 15% of the variation in the dependent variable 'export' is explained by the independent variables in model 6.

4.3.2 Cluster Strength

Cluster Specialization has a significant influence on export. As the ß-coefficient is positive (0.648), cluster specialization has a positive influence on export. The exp(ß) of Cluster Specialization is 1.911. As a consequence, for every increase in Cluster Specialization, it is 4.307 times more likely that this cluster has a medium or high innovation performance. Also cluster Focus has a significant effect on export (ß-coefficient is 0.221). The exp(ß) of Cluster Focus is 1.247. As a consequence, for every increase in Cluster Focus, it is 1.247 times more likely that this cluster has a medium or high innovation performance. Further, both cluster dummies (TwoStarDummy and ThreeStarDummy) show a significant result. OneStarDummy is used as a reference in the model. This means that two and three stars clusters show significant higher export performance than one star clusters. TwoStarDummy has a ß-coefficient of 1.188 and an exp(ß) of 1.625. This means that clusters with two stars are 7.878 times more likely to have a medium and high innovation performance than other industrial clusters. ThreeStarDummy has a ß-coefficient of 0,486 and an exp(ß) of 3.281. This means that clusters with three stars are 3.281 times more likely to have a medium and high innovation performance than other clusters.

4.3.3 Industries

Industry dummies show significant results in both models. Automotive industry and pharmaceutical industry both show positive ß-coefficients. In both models the exp(ß) for the industry dummies are situated in between 3.618 and 3.719. In the first model pharmaceutical industry has an exp(ß) of 3.701 (3.618 in model 2). Clusters related to the pharmaceutical industry are 3.701 times more likely to have medium and high innovation performance than other industrial clusters in the model. Clusters related to the automotive industry have an exp(ß) of 3.719 in model 1 (3.731 in model 2).

4.4 Results Model 7&8

An ordinal logistic regression is used to test the variables in model 7 and 8. The dependent variable export, which is used in both models, is an ordinal variable. Appendix 10 illustrates the outcome of the analysis of model 7. In the eighth model cluster indicators are used as independent variables.

Appendix 11 illustrated the outcome of the analysis. Further European country dummies are used as control variables in both models. The outcomes of both analyses are illustrated in table 6. Model 7 is illustrated on the left and model 8 is illustrated on the right.

Table 6 Models 7&8: Ordinal Logistic Regression

	Estimate	S.E.	Estimate	S.E.
Cluster Strength				
Size			0.048	0.034
Specialisation			**0.085	0.018
Focus			*0.033	0.015
TwoStarDummy	**0.294	0.064		
ThreeStarDummy	**0.915	0.123		
Industries				
Automotive	**0.639	0.201	**0.761	0.197
Pharmaceutical	**0.766	0.219	**0.760	0.219

Note: (*) means significant at 5% level, (**) means significant at 1% level
dependent variable is: Export (1)= low (2)=medium (3)=high
Controlled for country fixed effects (country dummies): yes

The results of table 6 correspond to the results of table 5. Model 7 and model 8 both show significant relationships between export and cluster indicators. In both models cluster specialization is positively related to innovation. Also cluster focus shows a significant positive relationship in both models. Cluster specialization has a coefficient of 0.085 and cluster focus has a coefficient of 0.033. An increasing value of cluster specialization or cluster focus will corresponds to an increasing probability of being in one of the higher outcome categories of export performance, as the coefficient of both indicators is positive.

Further, just like model 5, the outcome of model 7 shows significant results related to the relationship of cluster stars and export performance. The coefficient of two star clusters is 0.294 and that of three star clusters is 0.915. This means that clusters with two and three stars are more likely to be in the higher outcome categories of export performance than those with one star.

Both models show significant results regarding to industry dummies. Both, automotive and pharmaceutical industry, have significant higher export performance than other industries. The coefficient of the automotive industry is 0.639 and that of the pharmaceutical industry is 0.766. Clusters related to these particular two industries are more likely to be in the higher outcome categories of export performance than other industrial clusters in the model.

5. Discussion

The empirical results of the analysis are illustrated in chapter 4. In this chapter the results will be elaborated upon. First an overview is given of the empirical results. After this, the hypotheses which are formulated in the theoretical framework will be accepted or rejected.

5.1 Overview of the Results

An overview of the results of chapter 4 is given in table 7. The table shows whether there is a significant positive (+) or negative (-) influence of the independent variable on the dependent variable.

Table 7 Overview significant results

	Innovation	Export
Cluster Dummies: One Star Cluster Dummy is used as a reference		
Two Star Cluster Dummy	(+)	(+)
Three Star Cluster Dummy	(+)	(+)
Cluster indicators		
Cluster Size	(+)	
Cluster Specialization	(-)	(+)
Cluster Focus		(+)
Industry Dummies		
Automotive Industry Dummy		(+)
Pharmaceutical Industry Dummy	(+)	(+)

5.2 Cluster strength and innovation performance

Discussing the cluster indicators could give a better understanding with respect to the relationship between cluster strength and innovation. The results of the analyses show a significant positive relationship between cluster size and innovation. This is in line with the expectations that are touched upon in the literature part.

It is argued that firms and public institutions reach higher levels of innovation when they co-locate. European policymakers are concentrated on strengthening European clusters as it is assumed that this will spur innovation. As explained in paragraph 3.1, employment rates are used as main data for the calculation of the cluster indicators. The cluster indicators are assigned to a star-ratio which marks cluster strength. A higher amount of economic actors within the cluster will have a positive effect on the cluster strength (as explained in paragraph 2.2).

This research takes employment rate as a main indicator of cluster indicators. When there is a strong concentration of smaller firms, or the presence of larger firms within the cluster, employment rates in the specific region could rise. This leads to an explanation for the positive correlation between cluster size and innovation, as both, small and large firms are drivers of innovation. Small ventures often come up with new 'innovative' ideas, while large corporations possess financial recourses for R&D (see for example Acs and Audretsch, 1991).

The cluster indicators cluster 'specialization' is negatively related to innovation. This means that the probability of a lower innovation performance increases when the cluster gets more specialized (the cluster has a higher employment rate relatively to the rest of the concerning region than it would be expected when merely looking at the employment rate of the concerning industry in comparison with the rest of Europe). This result is not expected in the literature part. An argument for this result can be given regarding the cluster life cycle. The cluster lifecycle is the cluster dynamics of emergence; endurance and exhaustion (see Press, 2006). In paragraph 2.1 different stages of the cluster life cycle are discussed with the focus on the theory of Boschma (2007). He discerns four stages in the lifecycle of a cluster, namely: introductory stage; growth stage; maturity stage and decline stage. As explained, the number of economic actors is growing as the cluster is ageing. During the maturity stage firms are more depended on codified knowledge, while during the previous stage, firms are depended on tacit knowledge. When firms depend on tacit knowledge, the transfer and diffusion of it occurs slowly. As a result firms learn from using different kind of technologies and processes for absorbing this knowledge or transferring it. This is why firms obtain knowledge and skills when they depend on tacit knowledge. Eventually, this leads to higher innovation performance (Rosenberg, 1982). Despite this, as mentioned above, firms fall back on using codified knowledge in the maturity stage. The risk of lock-in effects lies in wait during this stage. As shown in paragraph 2.2 lock-in effects lead to lower innovation performance, as the cognitive distance between firms becomes smaller (Nootenboom, 2008). This is an explanation of why in later stages of the cluster lifecycle innovation performance is lower, while the employment rate can be high.

Further the results indicate that there is significant positive relationship between the 'cluster star' dummies and innovation performance. Two and three star clusters have higher innovation performance than one star clusters. This corresponds with the findings in the literature part. The results of the ordinal logistic regression analysis (table 3) show that clusters with two and three stars are more likely to have a higher innovation performance. This is why the first hypothesis is accepted.

<u>Accept</u> *Hypothesis #1: Cluster strength has a positive influence on innovation performance.*

5.3 Cluster strength and export performance

Discussing the cluster indicators could give a richer understanding with respect to the relationship between cluster strength and innovation. The results of the analyses show a positive relationship between cluster size and export. A higher cluster size indicates a higher amount of economic actors. In paragraph 2.2 is discussed that knowledge flows and spillovers occur in clusters. The more economic actors are involved in transactions, the more information will be exchanged. Weidersheim-Paul et. al (1978) argue that exporting depends on information exchange. Firms are stimulated to import and export if they are located near an information centre. Weidersheim-Paul et. al. (1978) argue that these firms are exposed to exogenous export stimuli. As explained in the literature part, the presence of exporting incumbents attracts other firms to co-locate. An important externality of co-location is the spillover of knowledge. Firms often establish near exporters, so they can benefit from export-spillovers and knowledge flows (United Nations, 2009). An Example of an export-spillover is the spillover of knowledge about foreign customers and foreign markets. Wiedersheim-Paul et. al. (1978) stress that exporting firms create positive attitudes towards non-exporting firms, especially when they are successful. Also Aitken et al. (1997) points out that export externalities drive co-location. According to him this is because export externalities, like export-spillovers, reduce the costs of access to foreign markets.

The analyses point out that 'cluster specialization' and 'cluster focus' have a significant positive influence on export. This result was expected in the literature part. Paragraph 2.3 discussed different arguments for the positive relationship between higher export rates and more specialized firms. More specialized economies arise as a consequence of redefined competitive advantages. Firms specialize in producing those products they have a competitive advantage in. As a consequence these products are heavily traded. As a result scale economies can be realized and stronger local concentration of activities occur (Storper, 2000).

As expected in the literature part, the results of the analyses show that two and three star clusters have significant higher export rates than those with one star. The conclusion is that cluster strength has a positive influence on export performance. The results of the analyses (table 7) show that clusters with two to three stars are more likely to have a higher export performance. This is why the second hypothesis is accepted.

Accept Hypothesis #2: Cluster strength has a positive influence on export performance.

5.4 Pharmaceutical industrial clusters and innovation

Table 7 shows that pharmaceutical clusters have significant higher innovation performance than other industrial clusters in the model. In paragraph 2.4 different arguments are discussed which support this result. The pharmaceutical sector is a knowledge-based industry as tacit knowledge and knowledge-spillovers play a crucial role (Busch, 2008). This is why in paragraph 2.4 is stated that geographic concentration is important for the maintenance of a competitive advantage. The results indicate that pharmaceutical clusters have significant higher innovation performance than other clusters, which is supported in the literature part. It is argued that innovation is a competitive advantage for pharmaceutical firms. Co-location is an important feature of the pharmaceutical industry, as geographic proximity of large and integrated pharmaceutical firms is crucial for the development of younger and smaller films in this industry (Dahlander and McKelvey, 2003). Literature also supports the idea that innovation is one of the most important characteristics of the pharmaceutical industry (see for example Audretch and Feldman, 1996; Swanson, 1995 and OECD, 2004). This leads to the acceptation of the third hypothesis.

Accept Hypothesis #3: Pharmaceutical clusters have higher innovation performance than other industrial clusters.

5.5 Automotive industrial clusters and export

Table 7 shows that automotive clusters have significant higher export performance than other industrial clusters in the model. In the literature part is argued that model-specific parts are produced close to final assembly plants (See Lung et al., 2004 and Lecler, 2002). As non model specific automotive parts seem to be produced at geographic distance, automotive clusters have high export rates. This is why the assumption is made that clusters related to the automotive industry have higher export performance than other industrial clusters. This assumption is supported by the results of the model. The model also shows that pharmaceutical clusters have significant higher export rates than other industrial clusters. An explanation which can be put forward is that as well as in the automotive industry, the pharmaceutical industry seems to locate the final stages of manufacturing in low cost areas (Taggart, 1993). Moreover, Taggart (1993) argues that the high costs of pharmaceutical R&D gives rise to the establishment of subsidiaries of pharmaceutical firms in foreign markets, as they have to cover the investment costs. This will spur export rates. This leads to the acceptation of the fourth hypothesis.

<u>*Accept*</u> *Hypothesis #4: Automotive clusters have higher export performancs than other industrial clusters.*

6. Conclusions and limitations

This thesis has attempted to explain the effect of cluster strength on innovation and export. The analysis is concentrated on European clusters. European cluster policies are focused on strengthening European clusters, by monitoring national and regional cluster policies. It is advocated in the theoretical framework that cluster strength leads to higher innovation and export performance. Four hypotheses were derived in the theoretical framework. The first hypothesis assumes cluster strength to have positive influence on innovation, while the second one assumes cluster strength to have a positive influence on export. The third hypothesis expected clusters related to the pharmaceutical industry to have higher innovation performance than other industrial clusters. The fourth hypothesis expected clusters related to the automotive industry to have higher export performance than other industrial clusters. According to these hypotheses, four conclusions are given below.

In the first place it is suggested in the theoretical framework that firms and public institutions can reach higher levels of innovation when they are co-located. High levels of competition drive the economic actors to innovate continuously in order to stay competitive in their geographic space. It is also argued that knowledge-flows and knowledge-spillovers accelerate a learning process. As suggested in the theoretical framework, the results of the conducted analysis show that there is a significant relationship between cluster strength and innovation.

In the second place, it is assumed in the theoretical framework that stronger clusters have higher export performance. Within strong clusters firms specialize in the production of specific product-parts. Firms co-locate in specific regions, instead of producing these particular parts everywhere. As a result these parts are exported, as often co-located firms are not established near customers. Marshall (1920) already argued in the previous century that knowledge is created in regional learning curves. According to him the most important knowledge-spillovers occur among firms within the same industry. This is why he argued that highly specialized locations experience higher levels of innovation, as well as higher levels of export. Results of the conducted analysis confirm that cluster strength has a positive effect on export performance.

In the third place, it is suggested in the theoretical framework that the pharmaceutical industry has a competitive advantage in innovation. This industry is involved in design, discovery and development of new cures. Firms active in this industry often collaborate with others in doing R&D. These firms seem to establish near universities or other research centers, because of the positive synergy effects co-location has. Geographic proximity is important in this sector to maintain innovative, therefore it is assumed that pharmaceutical clusters have higher innovation performance than other industrial clusters in the model. The results of the conducted analysis confirm that clusters related to the pharmaceutical industry have higher innovation performance than other industrial clusters.

In the fourth place, automotive firms are specialized in producing automotive parts or final assembly and as a consequence these components are heavily traded. In Europe there is a strong geographic concentration of automotive clusters. Automotive clusters are assumed to have higher export rates than other industrial clusters in the model. The results of the conducted analysis confirm that clusters related to automotive industry have higher export performance than other industrial clusters.

Tree limitations can be considered, which could encourage further research. The first limitation is that the conducted research is concentrated on European clusters, while a great part of the available literature about clusters and their performance is concentrated on clusters outside Europe. Further research could indicate whether the findings of this thesis count for industrial clusters outside Europe as well.

The second limitation is that exclusively employment rate is used as main variable to compute the cluster indicators. Although in the introduction the important role of other economic actors, like universities and research centers, is emphasized, the data is only focused on employees. Because employment data is available on a regional level and is rather easy obtainable through different databases, it is exclusively used as a main indicator for the calculation of the cluster indicators. However, additional data could have shown a more complete picture of cluster strength. Data which could be added to further research are for example salary and productivity indicators.

The third limitation is that all industrial sectors in Europe are included in the research. Edquist et.al. (2001) point out that categorizing manufacturing and service sectors is an important basis for classification of innovation, as the level of investment that firms make in their search for innovations differ. Therefore, further research about the relationship between innovation and cluster strength, could take into account a distinction between high technology, medium technology and low technology manufacturing sectors.

References

Association of Governments (1999) *Understanding cluster analysis.* San Diego

Acs Z. J. & Audretsch D. B. (1991) *Innovation and small firms,* Massachusetts: Institute of Technology

Aitken, B. Gordon H. & Ann H. 'Spillovers, Foreign Investment, and Export Behavior,' *Journal of International Economics* 43:1–2 (1997), 103–132.

Audretsch, D. B. (2001) The role of small firms in U.S. biotechnology clusters, *Small Business Economics* Vol 17, pp 3-15

Audretsch D. B. & Feldman M. P. (1996) 'R&D Spillovers and the Geography of Innovation and Production' *The American Economic Review*, Vol. 86, No. 3 (Jun., 1996), pp. 630-640

Bator, F. M. (1958) 'The anatomy of market failure' *The quarterly journal of economics* Vol. 72 No. 3, pp. 351-379

Becker H. (2006) *High noon in the automotive industry.* Berlin: Springer

Boschma R.A. (2005). 'Proximity and Innovation: A critical Assessment *'Regional Studies*, Vol. 39.1, pp. 61–74

Boschma R.A & ter Wal A.L.J (2007) 'Co-evolution of firms, industries and networks in space' *Papers is Evolutionary Geography* Vol. 07,07 pp1-19

Box, L & Engelhard, R (2006) Science *and technology policy for development.* London : Anthem Press

Brenner T. (2004) *Local industrial clusters existence, emergence and evolution*, London: Routledge

Breschi S. and Malerba F. (2005) Clusters, networks and innovation. New York: Oxford University Press

Brown J.S. & Duguid P. (2000). Mysteries of the region: knowledge dynamics in Silicon Valley. In: C. Lee, W.G. Miller, M.G. Hancock and H.S. Rowan *:The Silicon Valley Edge: A Habitat for innovation and Entrepreneurship.* Stanford: Stanford University Press, pp 16-39

Busch P. (2008) *Tacit knowledge in organizational learning.* Hershey: IGI Publishing

Cappellin R. & Orsenigo L. (2006) '*Regional learning networks in medium tech technologies and European integration'* 46th European Congress of the regional science association Paper n. 334

Chiesa V. & Chiaroni D. (2005) *Industrial clusters in biotechnology*. London: Imperial College Press

Christensen K. & Levinson D. (2003) *Encyclopedia of community.* Thousand Oaks: Sage Publications

Cooke P. (2001). 'Clusters ad Key Determinant of Economic Growth' *Nordregio*

Report Vol. 2 pp 23-38

Cohen J. , P. Cohen, S. G. West & L. S. Aiken (2003) *Applied multiple regression/correlation analysis for the behavioral sciences*, New Jersey: Lawrence Erlbaum Associates, Inc.

Cullen, W. C. & Dibner, M. D. (1993) Strategic alliances in biotechnology: imperatives for the 1990's. *Biotechnology Review* Vol 1, pp 110-119

Dahlander, L. & McKelvey, M. (2003) 'Proximity as a Factor in Biotechnology Research and Development' *Wirtschaftspolitische Blatter,* Vol. 3.

Dawn H. & Nigel P. (1998), The diffusion of innovations in central and eastern Europe: A study of determinants and impact of foreign direct investment, National Institute of Economic and Social Research: Londen

Edquist C., Hommen L., McKelvey M. (2001) *Innovation and employment* Edward Elgar Publishing Limited: Glos

Europe Cluster Observatory (2007) *European Cluster Memorandum* :*Promoting European innovation through clusters.* Luxembourg

European Commission (2006a) *Creating an innovative Europe.* Luxembourg

European Commission (2006b) *Putting knowledge into action.* Luxembourg

European Commission (2007) *Innovation clusters in Europe: A statistical analysis and overview of current policy support* Stockholm

European Commission (2008) *Case studies of clustering efforts in Europe: Analysis of their potential; for promoting innovation and competitiveness* Stockholm

European Commission (2009*) Fostering user-driven innovation through* Stockholm

European Commission (2009) *Knowledge intensive business services.* Stockholm

Fagerberg J., Mowery D.C. & Nelson R.R. (2005) *The Oxford handbook of innovation.* New York: Oxford University Press

Fan, Q., Li, K., Zeng, D. Z., Dong, Y. & Peng, R. (2009) *Development and the role of government* Washington: The World Bank

Feranti, D., Perry, G. E., Gill, I., Guasch, J. L., Maloney, W. F., Sanchez-Paramo, C. & Schady, N. (2003) *Closing the gab between education and technology* Washington: the World Bank

Filho W. L. , (2004) Trends in Innovation in a Europan Contact- Problems and Perspectives, TuTech, Harburger Schloßstrasse pp 6-12: Hamburg

Genton M. G. (2004) *Skew-elliptical disctributions and their applications: a journey beyond normality,* Boca Raton: Chapman & Hall/CRC

Gilbert B.A.& Kusar T.M. (2006) *The influence of geographic clusters and knowledge spillovers on the product innovation activities of new ventures.* Atlanta: Robinson College of Business, ISSN 16138333

Howells, J. R. L. (2002) Tacit knowledge, innovation and economic geography, *Urban Studies Vol 39.* pp 871-884

Jacobs J. (1969), *The economy of cites*, New York: Vintage

Katsikeas C. S. (1994) 'Export competitive advantages: The relevance of firm characteristics' *International Market Review:* Vol. 11 No. 3 pp33-53

Karlsson C., Johansson B. & Stough R. (2005) *Industrial clusters and inter-firm networks.* Glos: Edward Elgar Publishing Limited

Ketelhohn N. W. (2002) *The role of clusters as sources of dynamic externalities* UMI

Ketels C. (2004) European Clusters, *Structural Change in Europe 3 – Innovative City and Business Regions* pp 1-5

Krueger, A. O. (1990) 'Government failures in development' *The Journal of Economic Perspectives* Vol. 4 No 3, pp.9-23

Lagendijk A. (1998) *New Forms of regional industrial policy in Europe"how do policymakers understand competitiveness and clusters.* Unpublished manuscript, Newcastle: University of Newcastle

Lecler Y. (2002) 'The Cluster Role in the Development of theThai Car Industry' *International Journal of Urban and Regional Research* Vol. 26.4

Lieberman, M. B. (1989) 'The learning curve, technology barriers to entry and competitive survival in chemican processing industries, *Strategic Management Journal,* Vol. 10, pp. 431-447

Lin G.C.S. & Wang C. (2008) 'Technological Innovation in China's High-Tech Sector: Insights from a 2008 Survey of the Integrated Circuit Design Industry in Shanghai.*' Eurasian Geography and Economics.* Vol. 50, Number 4 pp 402-424

Lindqvist G. (2009) *Disentangling Clusters Agglomeration and Proximity Effects.* Stockholm: EFI, ISBN 978-91-7258-798-4

Lung, Y., Van Tulder, R. & Carillo, J. (2004) *Cars, cariiers of regionalism?* New York: Palgrave Macmillan

Madsen A., Smith V. & Dilling-Hansen M. (2004) *Industrial clusters, firm location and productivity.* Aarhus: University of Aarhus

Maggioni M.A. & Uberti T.E. (2009) 'Knowledge networks across Europe: which distance matters?' *The Annals of Regional Science.* Vol. 43, Iss. 3; pp. 691-721

Markusen, A. (1996), 'Sticky Places in Slippery Space: A Typology of Industrial Districts', *Economic Geography,* 72(3), pp. 293-313

Marshall A. (1920) Principles of Economics, Vol 8 London: Macmillan

McCullagh P. Nelder J. (1989). *Generalized Linear Models, Second Edition*. Chapman & Hall/CRC. ISBN 9780412317606

Monjon, S. & Waelbroeck P. (2003) 'The economics of intellectual property at universities' *International Journal of Industrial Organization* Vol. 21, Issue 9, Pages 1255-1270

Morrissey O. & Filatotchev I. (2001) Globalisation and trade. Londen: Frank Cass Publishers

Anklam P. (2007) *Network* Oxford: Butterworth-Heinemann

Nootenboom B. & van der Hoeven M. (2008) *Innovatie vernieuwd opening in viervoud*. Amsterdam: Amsterdam University Press

OECD (1997) *National Innovation systems*. Paris

OECD (2006a) Innovation in pharmaceutical biotechnology: Comparing national innovation systems at the sectoral level. Paris

OECD (2006b) Political Framework for Investment. Paris

Oxford Research AS *(2008) Cluster policy in Europe*. Kristiansand

Pezzini, M. & Byrne, E. (2007) *Globalization and regional economies: Can OECD regions compete in global industries?* Paris: OECD

Phlippen S. & van der Knaap B. (2007) *When Clusters become Networks* Unpublished manuscript, Rotterdam:Tinbergen institute

Porter M.E. (1990), *The competitive advantage of nations*. New York: Free Press

Porter M. E. (2003), 'The economics performance of regions' *Regional studies* Vol 37.6&7, pp549-578

Porter M. E. (2007) *Clusters and economic policy: aligning public policy with the new economics of competition.* Boston: Harvard Business School

Press, K. (2006) *A life cycle for clusters?* Heidelburg: Physica-Verlag

Raines, P. (2001) 'The cluster approach and the dynamics of regional policy making '*Regional and Industrial Policy Research Paper',* Vol 47

Radosevic S. (2004), Mismatch between demand an supply for technology: innovation, R&D and Growth Issues in Countries of Central and Eastern Europe, *Supporting the development of R&D and the innovation potential of post socialist countries*, pp 71-82

Rosenberg, N. (1982) *Inside the blackbox* Cambridge: Cambridge University Press

Schlegelmilch B.B. & Crook J. N. (1988) Firm-Level Determinants of Export Intensity *Managerial and Decision Economics*, Vol. 9, No. 4 pp. 291-300

Smith, A. (2007)*Wealth of Nations* (originally published in 1901), Cosimo, Inc. New York

Storper M. & Chen Y. (2000) *The effects of globalization on location of industries in the OECD and European Union*, DRUID Working Paper Vol 00-7, ISBN 87-7873-091-0

Sturgeon T., Biesebroeck J. Y. & Gereffi G. (2008) 'Value chains, networks and clusters: reframing the global automotive industry' *Journal of Economic Geography* Vol. 8 pp. 297–321

Solvell O. Lindqvist G.& Ketels C.(2003) *The cluster initiative Greenbook*, Stockholm: Bromma Truck AB

Swanson, T. M. (1995) *Intellectual property rights and biodiversity conversation* Cambridge: Cambridge University Press

Taghart, J. (1993) *The World Pharmaceutical industry* Londen: Routledge

Tschang F. and Vang J. (2008) *Explaining the spatial organization of creative industries: the case of the U.S Videogames industry.* Singapore: Singapore Management University

United Nations (2009) *Industrial Development Report.* Vienna

Uzzi B. (1997) 'Social structure and competition in interfirm networks: The paradox of embeddedness. *Administrative Science Quarterly,* Vol. 42 Issue 1 pp 35-67

Von Thunen (1826) The Isolated State, Vol 1 (translation: Peter. H. Von Thunen's Isolated State, Pergamon Press. 1966)

Wiedersheim-Paul F., Olson H. C. & Welch L. S. (1978) Pre-Export Activity: The First Step in Internationalization *Journal of International Business Studies*, Vol. 9, No. 1, pp. 47-58

Woolthuis, R.K., Lankhuizen, M. & Gilsing, V. (2005) 'A system failure framework for innovation policy design.' *Technovation* Vol. 25 Issue 6, pp 606-619

Zucker, L. G., Darby, M. R. & Brewer M. B. (1994) Intellectual capital and the birth of U.S. Biotechnology enterprises. *National Bureau of Economic Research* Working Paper No. 4653

Zukin S. And Di Maggio P. (1990) *Structures of Capital: The social organization of the economy*. New York: Campbridge University Press

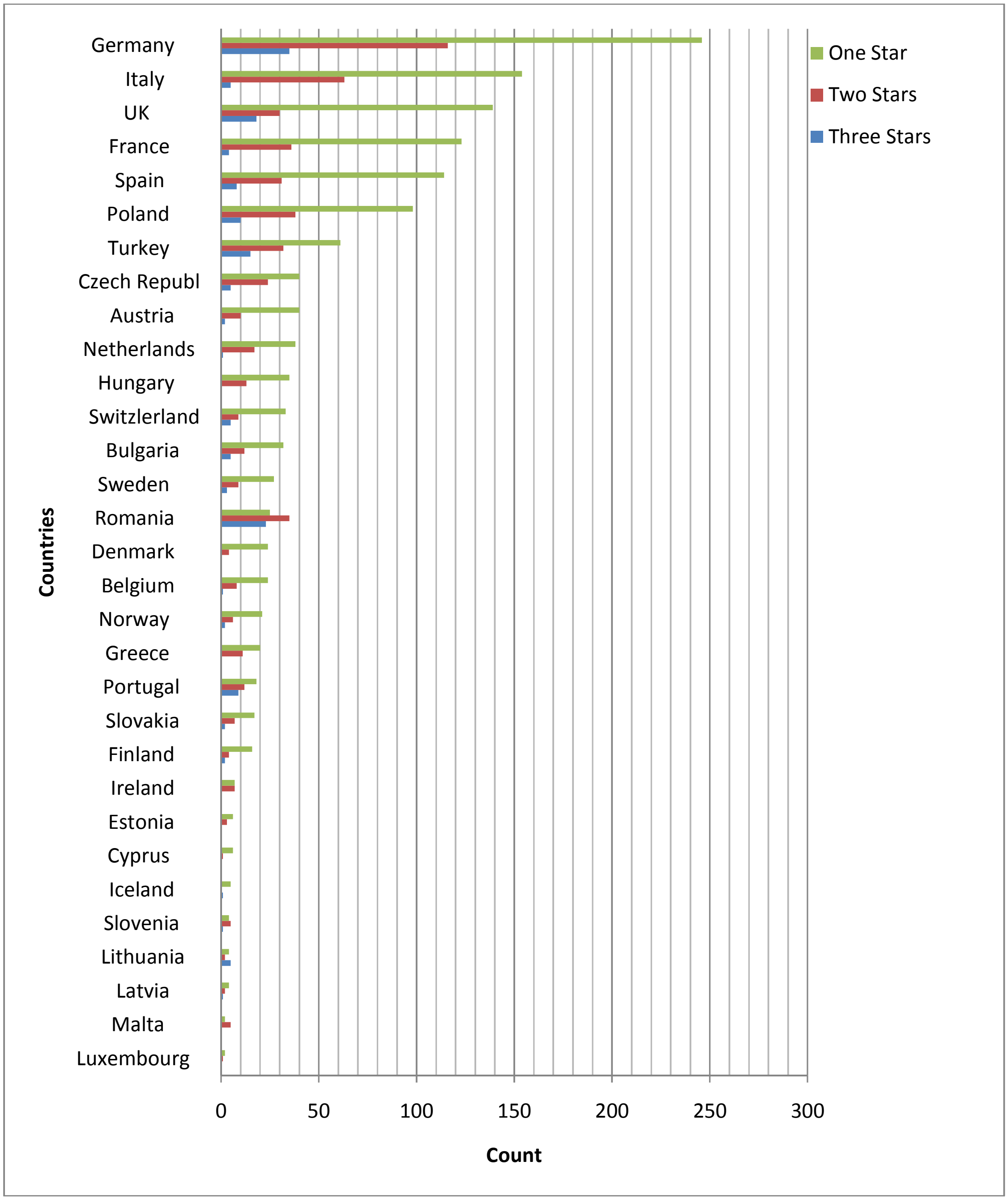
APPENDIX 1.1

Table 1 shows the number of three, two and one star clusters in the European member states. The data is illustrated in Figure 1.

Table 1

Country	Three Stars	Two Stars	One Star
Germany	35	116	246
Italy	5	63	154
UK	18	30	139
France	4	36	123
Spain	8	31	114
Poland	10	38	98
Turkey	15	32	61
Austria	2	10	40
Czech Republ	5	24	40
Netherlands	1	17	38
Hungary	0	13	35
Switzlerland	5	9	33
Bulgaria	5	12	32
Sweden	3	9	27
Romania	23	35	25
Belgium	1	8	24
Denmark	0	4	24
Norway	2	6	21
Greece	0	11	20
Portugal	9	12	18
Slovakia	2	7	17
Finland	2	4	16
Ireland	0	7	7
Cyprus	0	1	6
Estonia	0	3	6
Iceland	1	0	5
Latvia	1	2	4
Lithuania	5	2	4
Slovenia	1	5	4
Luxembourg	0	1	2
Malta	0	5	2

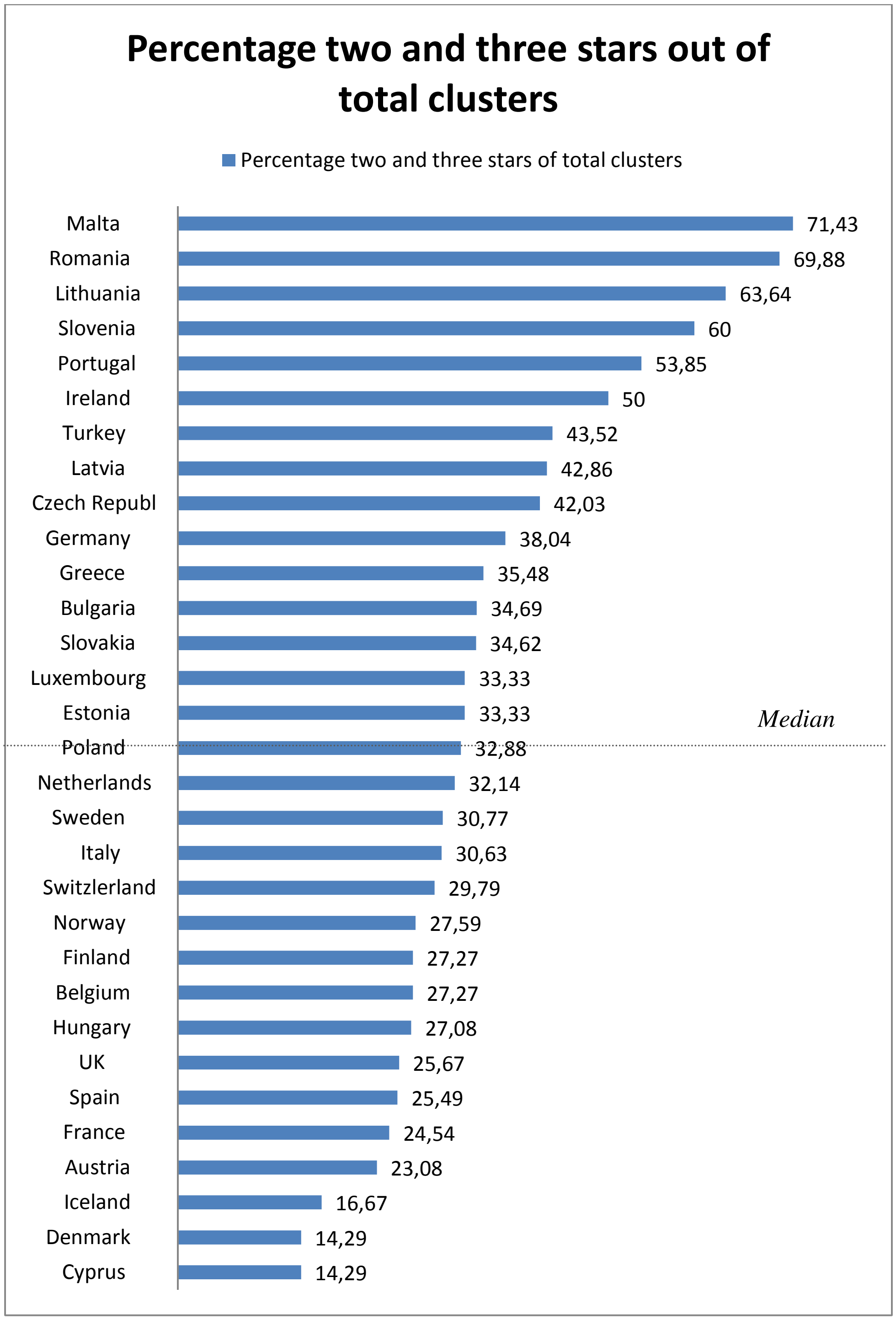
Figure 1


Germany
Italy
UK
France
Spain
Poland
Turkey
Czech Republ
Austria
Netherlands
Hungary
Switzlerland
Bulgaria
Sweden
Romania
Denmark
Belgium
Norway
Greece
Portugal
Slovakia
Finland
Ireland
Estonia
Cyprus
Iceland
Slovenia
Lithuania
Latvia
Malta
Luxembourg
Countries
0
50
100
150
200
250
300
Count
One Star
Two Stars
Three Stars

APPENDIX 1.2

Figure 2 shows the percentage of two and three star clusters out of total clusters in Europe.

Figure 2



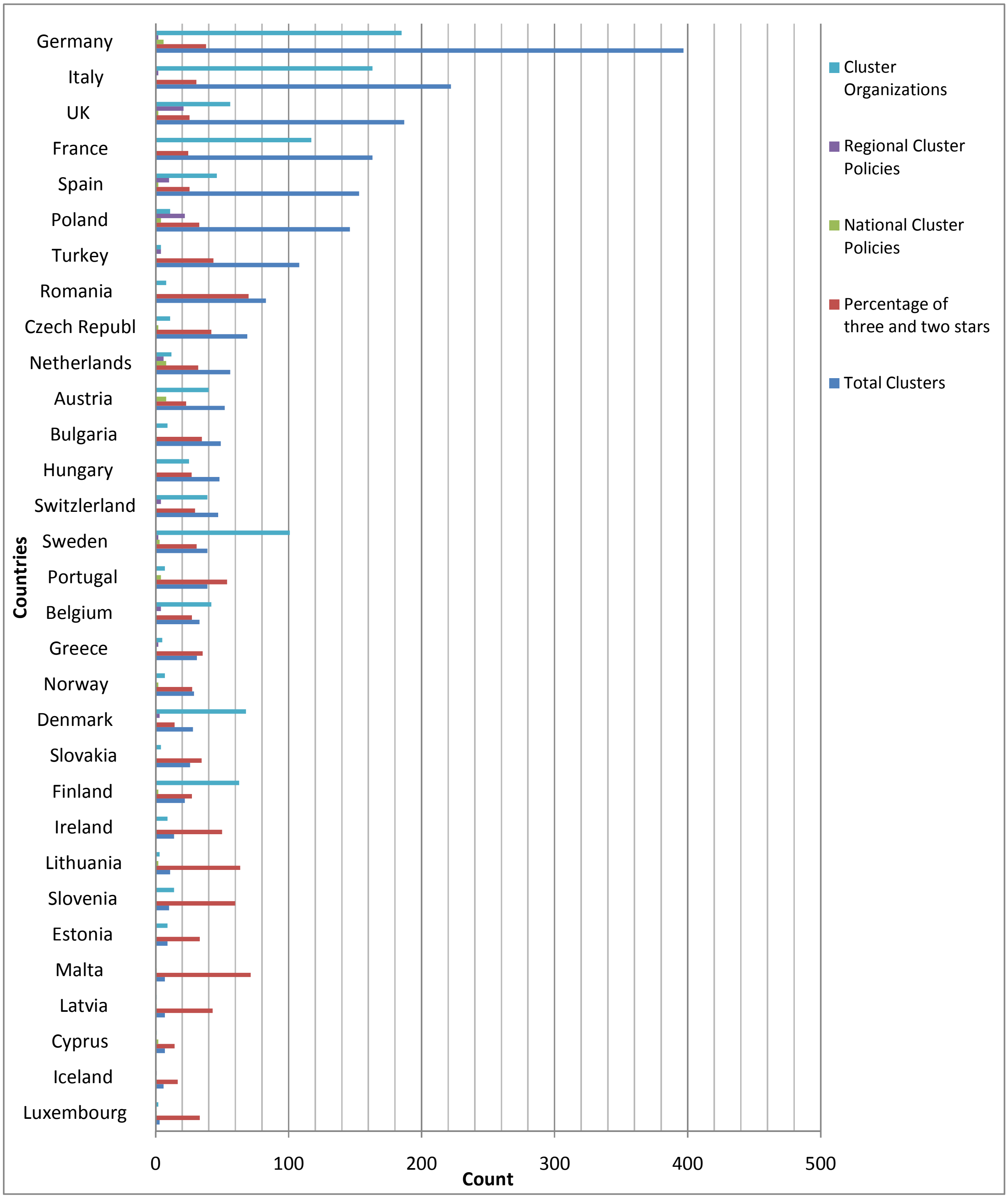
APPENDIX 1.3

Table 2 gives an overview of the cluster policies, regional cluster organizations and total clusters in Europe. This data is illustrated in Figure 3.

Table 2

Country	Total Clusters	Percentage of three and two stars	National Cluster Policies	Regional Cluster Policies	Cluster Organizations
Germany	397	38,04	6	2	185
Italy	222	30,63	0	2	163
UK	187	25,67	2	21	56
France	163	24,54	1	0	117
Spain	153	25,49	2	10	46
Poland	146	32,88	4	22	11
Turkey	108	43,52	0	4	4
Romania	83	69,88	1	0	8
Czech Republic	69	42,03	2	0	11
Netherlands	56	32,14	8	6	12
Austria	52	23,08	8	1	40
Bulgaria	49	34,69	1	0	9
Hungary	48	27,08	0	0	25
Switzlerland	47	29,79	0	4	39
Portugal	39	53,85	4	0	7
Sweden	39	30,77	3	2	101
Belgium	33	27,27	0	4	42
Greece	31	35,48	1	2	5
Norway	29	27,59	2	0	7
Denmark	28	14,29	1	3	68
Slovakia	26	34,62	1	0	4
Finland	22	27,27	2	0	63
Ireland	14	50	0	0	9
Lithuania	11	63,64	2	0	3
Slovenia	10	60	1	1	14
Estonia	9	33,33	1	1	9
Cyprus	7	14,29	2	0	1
Latvia	7	42,86	1	0	1
Malta	7	71,43	1	0	0
Iceland	6	16,67	0	1	0
Luxembourg	3	33,33	1	0	2

Figure 3


Countries
Germany
Italy
UK
France
Spain
Poland
Turkey
Romania
Czech Republ
Netherlands
Austria
Bulgaria
Hungary
Switzlerland
Sweden
Portugal
Belgium
Greece
Norway
Denmark
Slovakia
Finland
Ireland
Lithuania
Slovenia
Estonia
Malta
Latvia
Cyprus
Iceland
Luxembourg
0
100
200
300
400
500
Count
Cluster Organizations
Regional Cluster Policies
National Cluster Policies
Percentage of three and two stars
Total Clusters

APPENDIX 2

Table 3

Overview of the variables used in the analysis:

Variabel	Description	Kind of Variable
Dependent Variables		
InnDummy	Dummy for innovation. 1= high and medium innovation 0= low innovation	Dummy
ExDummy	Dummy for export 1= high and medium export 0= low export	Dummy
Innovation	1=weak 2=medium 3=strong	Ordinal
Export	1=weak 2=medium 3=strong	Ordinal
Independent Variables		
Size	Cluster size	Scale
Specialization	Cluster specialization	Scale
Focus	Cluster focus	Scale
Cluster Stars	1=1star 2=2star 3=3star	Ordinal
Dummy1star	Clusters with 1 star 1=1 star	Dummy
Dummy2star	Clusters with 2 stars 1=2 star	Dummy
Dummy3star	Clusters with 3 stars 1=3 star	Dummy
Dummy1	Automotive industry (=1)	Dummy
Dummy2	Pharmaceutical industry (=1)	Dummy
Control Variables		
Country dummies	EU-27 member states, Turkey, Swtzerland, Norway and Iceland	Dummy

APPENDIX 3

Table 1

Correlation Matrix

		Constant	Size	Specialisation	Focus	Dummy1	Dummy2	Dummy Belgium	DummyCzech	DummySpain	Dummy France	DummyItaly	Dummy Poland	DummyUK	Dummy Portugal
Step 1	Constant	1,000	-,038	-,201	-,325	,025	-,019	,000	-,667	-,721	-,656	-,737	-,568	,000	-,338
	Size	-,038	1,000	-,683	,170	,061	-,038	,000	-,007	-,300	-,060	-,246	-,007	,000	-,181
	Specialisation	-,201	-,683	1,000	-,158	-,119	,011	,000	-,040	,254	,075	,214	,010	,000	,046
	Focus	-,325	,170	-,158	1,000	-,171	,069	,000	-,085	-,005	-,080	,006	-,048	,000	-,104
	Dummy1	,025	,061	-,119	-,171	1,000	-,001	,000	,037	-,016	,021	,008	,048	,000	,052
	Dummy2	-,019	-,038	,011	,069	-,001	1,000	,000	-,024	,005	-,031	,013	-,096	,000	,003
	DummyBelgium	,000	,000	,000	,000	,000	,000	1,000	,000	,000	,000	,000	,000	,000	,000
	DummyCzech	-,667	-,007	-,040	-,085	,037	-,024	,000	1,000	,630	,615	,641	,537	,000	,385
	DummySpain	-,721	-,300	,254	-,005	-,016	,005	,000	,630	1,000	,610	,709	,517	,000	,402
	DummyFrance	-,656	-,060	,075	-,080	,021	-,031	,000	,615	,610	1,000	,617	,501	,000	,356
	DummyItaly	-,737	-,246	,214	,006	,008	,013	,000	,641	,709	,617	1,000	,525	,000	,400
	DummyPoland	-,568	-,007	,010	-,048	,048	-,096	,000	,537	,517	,501	,525	1,000	,000	,305
	DummyUK	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	1,000	,000
	DummyPortugal	-,338	-,181	,046	-,104	,052	,003	,000	,385	,402	,356	,400	,305	,000	1,000
	DummyDenmark	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	DummyCyprus	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	DummyBulgaria	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	DummySlovakia	-,381	-,009	-,011	-,012	-,039	,000	,000	,365	,352	,338	,357	,293	,000	,208
	DummyLithuania	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	DummyGreece	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	DummyEstonia	-,193	,004	-,028	-,004	,024	,000	,000	,191	,178	,174	,182	,153	,000	,110
	DummyAustria	-,407	,062	-,047	-,084	,054	-,018	,000	,410	,365	,377	,376	,331	,000	,224
	DummyHungary	-,491	-,006	,013	,000	-,007	-,060	,000	,447	,436	,418	,443	,367	,000	,251
	DummyFinland	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	DummySweden	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	DummyLuxembourg	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	DummyMalta	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	DummySlovenia	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
	DummyLatvia	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000

Dummy Denmark	Dummy Cyprus	Dummy Bulgaria	Dummy Slovakia	Dummy Lithuania	Dummy Greece	Dummy Estonia	Dummy Austria	Dummy Hungary	Dummy Finland	Dummy Sweden	Dummy Luxembourg	DummyMalta	Dummy Slovenia	DummyLatvia
,000	,000	,000	-,381	,000	,000	-,193	-,407	-,491	,000	,000	,000	,000	,000	,000
,000	,000	,000	-,009	,000	,000	,004	,062	-,006	,000	,000	,000	,000	,000	,000
,000	,000	,000	-,011	,000	,000	-,028	-,047	,013	,000	,000	,000	,000	,000	,000
,000	,000	,000	-,012	,000	,000	-,004	-,084	,000	,000	,000	,000	,000	,000	,000
,000	,000	,000	-,039	,000	,000	,024	,054	-,007	,000	,000	,000	,000	,000	,000
,000	,000	,000	,000	,000	,000	,000	-,018	-,060	,000	,000	,000	,000	,000	,000
,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
,000	,000	,000	,365	,000	,000	,191	,410	,447	,000	,000	,000	,000	,000	,000
,000	,000	,000	,352	,000	,000	,178	,365	,436	,000	,000	,000	,000	,000	,000
,000	,000	,000	,338	,000	,000	,174	,377	,418	,000	,000	,000	,000	,000	,000
,000	,000	,000	,357	,000	,000	,182	,376	,443	,000	,000	,000	,000	,000	,000
,000	,000	,000	,293	,000	,000	,153	,331	,367	,000	,000	,000	,000	,000	,000
,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
,000	,000	,000	,208	,000	,000	,110	,224	,251	,000	,000	,000	,000	,000	,000
1,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
,000	1,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
,000	,000	1,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
,000	,000	,000	1,000	,000	,000	,104	,221	,247	,000	,000	,000	,000	,000	,000
,000	,000	,000	,000	1,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
,000	,000	,000	,000	,000	1,000	,000	,000	,000	,000	,000	,000	,000	,000	,000
,000	,000	,000	,104	,000	,000	1,000	,116	,127	,000	,000	,000	,000	,000	,000
,000	,000	,000	,221	,000	,000	,116	1,000	,273	,000	,000	,000	,000	,000	,000
,000	,000	,000	,247	,000	,000	,127	,273	1,000	,000	,000	,000	,000	,000	,000
,000	,000	,000	,000	,000	,000	,000	,000	,000	1,000	,000	,000	,000	,000	,000
,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	1,000	,000	,000	,000	,000
,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	1,000	,000	,000	,000
,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	1,000	,000	,000
,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	1,000	,000
,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	1,000

Table 2

Variance Inflation Factor

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	size ratio	,546	1,830
	specialisation ratio	,628	1,592
	focus ratio	,722	1,385
	Automitive dummy	,936	1,068
	Biopharma dummy	,879	1,138
	DummyBelgium	,695	1,439
	DummySpain	,335	2,983
	DummyFrance	,337	2,967
	DummyItaly	,281	3,563
	DummyPoland	,381	2,624
	DummyUK	,315	3,175
	DummyPortugal	,672	1,488
	DummyDenmark	,716	1,397
	DummyCyprus	,914	1,094
	DummyBulgaria	,866	1,155
	DummySlovakia	,750	1,333
	DummyLithuania	,869	1,151
	DummyGreece	,859	1,164
	DummyEstonia	,885	1,130
	DummyAustria	,591	1,692
	DummySweden	,726	1,377
	DummyHungary	,622	1,607
	DummyFinland	,780	1,282
	DummyLuxembourg	,955	1,048
	DummyMalta	,913	1,095
	DummySlovenia	,884	1,131

DummyLatvia	,916	1,092
DummyGermany	,205	4,887
number of starts	,570	1,754

a. Dependent Variable: strength of innovation

APPENDIX 4

Logistic Regression

Model 1

Block 0: Beginning Block

Classification Table[a,b]

Observed			Predicted		
			MediumHightInnDummy		Percentage Correct
			0	1	
Step 0	MediumHightInnDummy	0	0	498	,0
		1	0	1177	100,0
	Overall Percentage				70,3

a. Constant is included in the model.

b. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	,860	,053	258,889	1	,000	2,363

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	873,860	27	,000
	Block	873,860	27	,000
	Model	873,860	27	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1164,852[a]	,406	,577

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Classification Table[a]

Observed			Predicted		
			MediumHightInnDummy		Percentage Correct
			0	1	
Step 1	MediumHightInnDummy	0	351	147	70,5
		1	114	1063	90,3
	Overall Percentage				84,4

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Dummy1	,202	,452	,201	1	,654	1,224
	Dummy2	2,064	,903	5,230	1	,022	7,878
	DummyBelgium	21,955	6938,806	,000	1	,997	3,427E9
	DummyCzech	3,078	,307	100,729	1	,000	21,705
	DummySpain	,747	,298	6,289	1	,012	2,110
	DummyFrance	2,402	,330	52,987	1	,000	11,044
	DummyItaly	1,982	,300	43,628	1	,000	7,255
	DummyPoland	-1,417	,382	13,726	1	,000	,243
	DummyUK	22,025	2937,908	,000	1	,994	3,675E9
	DummyPortugal	-,850	,519	2,688	1	,101	,427
	DummyDenmark	22,008	7559,891	,000	1	,998	3,613E9

DummyCyprus	-20,358	15189,246	,000	1	,999	,000
DummyBulgaria	19,961	23199,421	,000	1	,999	4,667E8
DummySlovakia	-,643	,558	1,326	1	,250	,526
DummyLithuania	-20,473	12109,596	,000	1	,999	,000
DummyGreece	21,926	11479,507	,000	1	,998	3,328E9
DummyEstonia	3,024	1,084	7,778	1	,005	20,572
DummyAustria	2,891	,502	33,121	1	,000	18,003
DummyHungary	-,712	,454	2,461	1	,117	,491
DummySweden	21,984	7423,923	,000	1	,998	3,527E9
DummyFinland	22,024	8565,760	,000	1	,998	3,673E9
DummyLuxembourg	22,025	23199,421	,000	1	,999	3,676E9
DummyMalta	-20,377	15187,783	,000	1	,999	,000
DummySlovenia	21,981	12704,798	,000	1	,999	3,518E9
DummyLatvia	-20,412	15183,328	,000	1	,999	,000
ThreeStarDummy	,235	,337	,487	1	,485	1,265
TwoStarDummy	,129	,174	,552	1	,458	1,138
Constant	-,864	,260	11,047	1	,001	,421

Appendix 5

Model 2

Logistic Regression

Block 0: Beginning Block

Classification Table[a,b]

Observed			Predicted		
			MediumHightInnDummy		Percentage Correct
			0	1	
Step 0	MediumHightInnDummy	0	0	498	,0
		1	0	1176	100,0
	Overall Percentage				70,3

a. Constant is included in the model.

b. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	,859	,053	258,312	1	,000	2,361

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	1042,619	28	,000
	Block	1042,619	28	,000
	Model	1042,619	28	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	995,387[a]	,464	,658

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Classification Table[a]

Observed			Predicted		
			MediumHightInnDummy		Percentage Correct
			0	1	
Step 1	MediumHightInnDummy	0	358	140	71,9
		1	98	1078	91,7
	Overall Percentage				85,8

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Dummy1	,647	,511	1,605	1	,205	1,910
	Dummy2	1,624	,898	3,273	1	,070	5,075
	DummyBelgium	20,738	6774,664	,000	1	,998	1,015E9
	DummyCzech	3,257	,315	106,635	1	,000	25,983
	DummySpain	-,514	,340	2,280	1	,131	,598
	DummyFrance	2,227	,347	41,220	1	,000	9,271
	DummyItaly	,940	,328	8,217	1	,004	2,561
	DummyPoland	-1,324	,390	11,541	1	,001	,266
	DummyUK	22,040	2797,172	,000	1	,994	3,731E9
	DummyPortugal	-1,330	,541	6,041	1	,014	,264
	DummyDenmark	19,849	7565,052	,000	1	,998	4,173E8
	DummyCyprus	-19,605	15183,548	,000	1	,999	,000

DummyBulgaria	18,577	22683,398	,000	1	,999	1,170E8
DummySlovakia	-,627	,568	1,220	1	,269	,534
DummyLithuania	-20,901	12106,038	,000	1	,999	,000
DummyGreece	20,439	11510,496	,000	1	,999	7,529E8
DummyEstonia	2,951	1,089	7,343	1	,007	19,128
DummyAustria	4,096	,542	57,198	1	,000	60,075
DummyHungary	-,677	,470	2,076	1	,150	,508
DummySweden	22,416	7074,643	,000	1	,997	5,436E9
DummyFinland	22,361	8107,398	,000	1	,998	5,144E9
DummyLuxembourg	23,500	23195,898	,000	1	,999	1,606E10
DummyMalta	-18,464	15183,438	,000	1	,999	,000
DummySlovenia	21,556	12702,738	,000	1	,999	2,299E9
DummyLatvia	-21,104	15188,030	,000	1	,999	,000
SizeLog	1,460	,139	110,986	1	,000	4,307
SpecializationLog	-1,456	,179	66,045	1	,000	,233
FocusLog	,109	,090	1,456	1	,228	1,115
Constant	,840	,305	7,594	1	,006	2,316

APPENDIX 6

Model 3

PLUM - Ordinal Regression

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1519,111			
Final	,000	1519,111	27	,000

Link function: Complementary Log-log.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	361,247	169	,000
Deviance	407,060	169	,000

Link function: Complementary Log-log.

Pseudo R-Square

Cox and Snell	,596
Nagelkerke	,671
McFadden	,414

Link function: Complementary Log-log.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Innovation = 1]	2,350	5,674	,171	1	,679	-8,772	13,471
	[Innovation = 2]	3,954	5,675	,485	1	,486	-7,169	15,076
Location	[DummyBelgium=0]	2,303	,340	45,916	1	,000	1,637	2,970
	[DummyBelgium=1]	0[a]	.	.	0	.	.	.

	[DummySwitzerland=1]	0[a]	.	.	0	.	.	.
	[DummyCzech=0]	1,791	,159	126,766	1	,000	1,479	2,103
	[DummyCzech=1]	0[a]	.	.	0	.	.	.
	[DummySpain=0]	,728	,166	19,296	1	,000	,403	1,053
	[DummySpain=1]	0[a]	.	.	0	.	.	.
	[DummyFrance=0]	1,331	,173	59,428	1	,000	,993	1,670
	[DummyFrance=1]	0[a]	.	.	0	.	.	.
	[DummyItaly=0]	,586	,159	13,559	1	,000	,274	,898
	[DummyItaly=1]	0[a]	.	.	0	.	.	.
	[DummyPoland=0]	-1,086	,178	37,127	1	,000	-1,436	-,737
	[DummyPoland=1]	0[a]	.	.	0	.	.	.
	[DummyRomania=1]	0[a]	.	.	0	.	.	.
	[DummyUK=0]	2,287	,191	143,370	1	,000	1,913	2,661
	[DummyUK=1]	0[a]	.	.	0	.	.	.
	[DummyTurkey=1]	0[a]	.	.	0	.	.	.
	[DummyPortugal=0]	-,894	,251	12,657	1	,000	-1,387	-,402
	[DummyPortugal=1]	0[a]	.	.	0	.	.	.
	[DummyNetherlands=1]	0[a]	.	.	0	.	.	.
	[DummyIreland=1]	0[a]	.	.	0	.	.	.
	[DummyDenmark=0]	11,140	24,741	,203	1	,653	-37,352	59,633
	[DummyDenmark=1]	0[a]	.	.	0	.	.	.
	[DummyCyprus=1]	2,523	5,676	,198	1	,657	-8,601	13,648
	[DummyCyprus=2]	0[a]	.	.	0	.	.	.
	[DummyBulgaria=0]	,907	,811	1,251	1	,263	-,683	2,497
	[DummyBulgaria=1]	0[a]	.	.	0	.	.	.
	[DummySlovakia=0]	,233	,265	,775	1	,379	-,286	,752
	[DummySlovakia=1]	0[a]	.	.	0	.	.	.
	[DummyLithuania=0]	-2,716	4,492	,365	1	,545	-11,520	6,088
	[DummyLithuania=1]	0[a]	.	.	0	.	.	.
	[DummyGreece=0]	,637	,361	3,117	1	,077	-,070	1,344
	[DummyGreece=1]	0[a]	.	.	0	.	.	.
	[DummyEstonia=0]	,569	,387	2,160	1	,142	-,190	1,329
	[DummyEstonia=1]	0[a]	.	.	0	.	.	.
	[DummyAustria=0]	1,088	,216	25,399	1	,000	,665	1,511
	[DummyAustria=1]	0[a]	.	.	0	.	.	.

[DummyHungary=0]	,181	,217	,695	1	,405	-,244	,605
[DummyHungary=1]	0[a]	.	.	0	.	.	.
[DummySweden=0]	3,590	,597	36,122	1	,000	2,419	4,761
[DummySweden=1]	0[a]	.	.	0	.	.	.
[DummyFinland=0]	3,304	,598	30,517	1	,000	2,132	4,477
[DummyFinland=1]	0[a]	.	.	0	.	.	.
[DummyNorway=1]	0[a]	.	.	0	.	.	.
[DummyLuxembourg=0]	,673	,677	,988	1	,320	-,654	2,001
[DummyLuxembourg=1]	0[a]	.	.	0	.	.	.
[DummyMalta=0]	-2,559	5,668	,204	1	,652	-13,668	8,551
[DummyMalta=1]	0[a]	.	.	0	.	.	.
[DummyLatvia=0]	-2,631	5,660	,216	1	,642	-13,724	8,462
[DummyLatvia=1]	0[a]	.	.	0	.	.	.
[DummySlovenia=0]	,612	,389	2,469	1	,116	-,151	1,374
[DummySlovenia=1]	0[a]	.	.	0	.	.	.
[DummyGermany=0]	0[a]	.	.	0	.	.	.
[DummyGermany=1]	0[a]	.	.	0	.	.	.
[DummyIceland=1]	0[a]	.	.	0	.	.	.
[Dummy1=0]	,097	,212	,208	1	,649	-,319	,512
[Dummy1=1]	0[a]	.	.	0	.	.	.
[Dummy2=0]	,483	,290	2,779	1	,096	-,085	1,051
[Dummy2=1]	0[a]	.	.	0	.	.	.
[Stars=1]	,320	,150	4,544	1	,033	,026	,613
[Stars=2]	,186	,078	5,668	1	,017	,033	,339
[Stars=3]	0[a]	.	.	0	.	.	.

Link function: Complementary Log-log.

a. This parameter is set to zero because it is redundant.
b. For Dummies in this model: 0=yes 1=no
c. For Stars: 1=3 stars 2=2stars 3=1star

Appendix 7

Model 4

PLUM - Ordinal Regression

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	3663,869			
Final	1094,323	2569,546	28	,000

Link function: Complementary Log-log.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	3257,308	3314	,756
Deviance	2611,419	3314	1,000

Link function: Complementary Log-log.

Pseudo R-Square

Cox and Snell	,785
Nagelkerke	,883
McFadden	,701

Link function: Complementary Log-log.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[Innovation = 1]	2,828	,152	344,767	1	,000	2,529	3,126
	[Innovation = 2]	4,502	,155	838,974	1	,000	4,198	4,807
Location	Size	,478	,049	94,652	1	,000	,381	,574
	Specialisation	-,140	,020	50,532	1	,000	-,179	-,102
	Focus	-,024	,018	1,794	1	,180	-,060	,011
	[DummyBelgium=0]	1,949	,336	33,561	1	,000	1,290	2,609

[DummyBelgium=1]	0[a]	.	.	0	.	.	.
[DummySwitzerland=1]	0[a]	.	.	0	.	.	.
[DummyCzech=0]	1,763	,161	119,572	1	,000	1,447	2,080
[DummyCzech=1]	0[a]	.	.	0	.	.	.
[DummySpain=0]	,346	,171	4,084	1	,043	,010	,682
[DummySpain=1]	0[a]	.	.	0	.	.	.
[DummyFrance=0]	1,024	,174	34,791	1	,000	,683	1,364
[DummyFrance=1]	0[a]	.	.	0	.	.	.
[DummyItaly=0]	,054	,167	,103	1	,749	-,274	,382
[DummyItaly=1]	0[a]	.	.	0	.	.	.
[DummyPoland=0]	-1,164	,183	40,445	1	,000	-1,523	-,806
[DummyPoland=1]	0[a]	.	.	0	.	.	.
[DummyRomania=1]	0[a]	.	.	0	.	.	.
[DummyUK=0]	2,273	,194	137,408	1	,000	1,893	2,653
[DummyUK=1]	0[a]	.	.	0	.	.	.
[DummyTurkey=1]	0[a]	.	.	0	.	.	.
[DummyPortugal=0]	-1,054	,265	15,840	1	,000	-1,573	-,535
[DummyPortugal=1]	0[a]	.	.	0	.	.	.
[DummyNetherlands=1]	0[a]	.	.	0	.	.	.
[DummyIreland=1]	0[a]	.	.	0	.	.	.
[DummyDenmark=0]	20,572	3663,225	,000	1	,996	-7159,216	7200,361
[DummyDenmark=1]	0[a]	.	.	0	.	.	.
[DummyCyprus=1]	3,161	,000	.	1	.	3,161	3,161
[DummyCyprus=2]	0[a]	.	.	0	.	.	.
[DummyBulgaria=0]	,220	,845	,068	1	,794	-1,435	1,875
[DummyBulgaria=1]	0[a]	.	.	0	.	.	.
[DummySlovakia=0]	,374	,266	1,973	1	,160	-,148	,896
[DummySlovakia=1]	0[a]	.	.	0	.	.	.
[DummyLithuania=0]	-3,527	386,237	,000	1	,993	-760,537	753,482
[DummyLithuania=1]	0[a]	.	.	0	.	.	.
[DummyGreece=0]	,268	,364	,540	1	,462	-,446	,981
[DummyGreece=1]	0[a]	.	.	0	.	.	.
[DummyEstonia=0]	,567	,390	2,114	1	,146	-,197	1,332
[DummyEstonia=1]	0[a]	.	.	0	.	.	.
[DummyAustria=0]	1,188	,218	29,741	1	,000	,761	1,615

[DummyAustria=1]	0[a]	.	.	0	.	.	.
[DummyHungary=0]	,022	,221	,010	1	,920	-,411	,455
[DummyHungary=1]	0[a]	.	.	0	.	.	.
[DummySweden=0]	3,597	,597	36,281	1	,000	2,426	4,767
[DummySweden=1]	0[a]	.	.	0	.	.	.
[DummyFinland=0]	3,323	,598	30,927	1	,000	2,152	4,494
[DummyFinland=1]	0[a]	.	.	0	.	.	.
[DummyNorway=1]	0[a]	.	.	0	.	.	.
[DummyLuxembourg=0]	,935	,687	1,852	1	,174	-,412	2,281
[DummyLuxembourg=1]	0[a]	.	.	0	.	.	.
[DummyMalta=0]	-3,116	481,467	,000	1	,995	-946,774	940,542
[DummyMalta=1]	0[a]	.	.	0	.	.	.
[DummyLatvia=0]	-3,823	442,085	,000	1	,993	-870,293	862,647
[DummyLatvia=1]	0[a]	.	.	0	.	.	.
[DummySlovenia=0]	,555	,390	2,021	1	,155	-,210	1,320
[DummySlovenia=1]	0[a]	.	.	0	.	.	.
[DummyGermany=0]	0[a]	.	.	0	.	.	.
[DummyGermany=1]	0[a]	.	.	0	.	.	.
[DummyIceland=1]	0[a]	.	.	0	.	.	.
[Dummy1=0]	,287	,213	1,820	1	,177	-,130	,705
[Dummy1=1]	0[a]	.	.	0	.	.	.
[Dummy2=0]	,296	,288	1,053	1	,305	-,269	,860
[Dummy2=1]	0[a]	.	.	0	.	.	.

Link function: Complementary Log-log.

a. This parameter is set to zero because it is redundant.

d. For Dummies in this model: 0=yes 1=no

Appendix 8

Model 5

Logistic Regression

Block 0: Beginning Block

Classification Table[a,b]

	Observed		Predicted MediumHighExDummy 0	1	Percentage Correct
Step 0	MediumHighExDummy	0	0	701	,0
		1	0	1094	100,0
	Overall Percentage				60,9

a. Constant is included in the model.

b. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	,445	,048	84,638	1	,000	1,561

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	181,625	34	,000
	Block	181,625	34	,000
	Model	181,625	34	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	2220,028[a]	,096	,130

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Classification Table[a]

Observed			Predicted		
			MediumHighExDummy		Percentage Correct
			0	1	
Step 1	MediumHighExDummy	0	347	354	49,5
		1	276	818	74,8
	Overall Percentage				64,9

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Dummy1	1,333	,453	8,659	1	,003	3,791
	Dummy2	1,310	,463	8,015	1	,005	3,708
	DummyBelgium	-1,320	,487	7,342	1	,007	,267
	DummySwitzerland	-,596	,441	1,827	1	,176	,551
	DummyCzech	-,966	,311	9,647	1	,002	,381
	DummySpain	-1,013	,339	8,910	1	,003	,363
	DummyFrance	-,566	,338	2,800	1	,094	,568
	DummyItaly	-1,056	,326	10,497	1	,001	,348
	DummyPoland	-,704	,345	4,159	1	,041	,495
	DummyRomania	-1,079	,384	7,913	1	,005	,340
	DummyUK	,058	,357	,026	1	,871	1,060
	DummyTurkey	-,900	,362	6,182	1	,013	,406
	DummyPortugal	-,120	,531	,051	1	,822	,887

	DummyNetherlands	-1,014	,414	6,002	1	,014	,363
	DummyIreland	-1,508	,622	5,878	1	,015	,221
	DummyDenmark	-,798	,506	2,487	1	,115	,450
	DummyCyprus	-,959	,870	1,215	1	,270	,383
	DummyBulgaria	1,448	,668	4,696	1	,030	4,256
	DummySlovakia	-,181	,569	,101	1	,751	,835
	DummyLithuania	,856	1,106	,599	1	,439	2,353
	DummyGreece	-1,113	,492	5,108	1	,024	,329
	DummyEstonia	-,543	,790	,472	1	,492	,581
	DummyAustria	,857	,528	2,636	1	,104	2,356
	DummyHungary	-1,568	,440	12,724	1	,000	,208
	DummySweden	,502	,701	,514	1	,473	1,653
	DummyFinland	-,296	,619	,229	1	,632	,743
	DummyNorway	-,067	,602	,012	1	,912	,935
	DummyLuxembourg	20,098	28249,964	,000	1	,999	5,352E8
	DummyMalta	,586	1,137	,265	1	,606	1,796
	DummySlovenia	,006	,860	,000	1	,994	1,006
	DummyLatvia	,330	1,160	,081	1	,776	1,391
	DummyIceland	-1,163	1,073	1,176	1	,278	,312
	ThreeStarDummy	1,188	,232	26,324	1	,000	3,281
	TwoStarDummy	,486	,118	16,815	1	,000	1,625
	Constant	,879	,294	8,965	1	,003	2,408

Appendix 9

Model 6

Logistic Regression

Block 0: Beginning Block

Classification Table[a,b]

Observed			Predicted		
			MediumHighExDummy		Percentage Correct
			0	1	
Step 0	MediumHighExDummy	0	0	701	,0
		1	0	1093	100,0
	Overall Percentage				60,9

a. Constant is included in the model.

b. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	,444	,048	84,260	1	,000	1,559

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	206,891	35	,000
	Block	206,891	35	,000
	Model	206,891	35	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	2193,772[a]	,109	,148

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Classification Table[a]

	Observed		Predicted		
			MediumHighExDummy		Percentage Correct
			0	1	
Step 1	MediumHighExDummy	0	304	397	43,4
		1	181	912	83,4
	Overall Percentage				67,8

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Dummy1	1,317	,452	8,491	1	,004	3,731
	Dummy2	1,286	,465	7,644	1	,006	3,618
	DummyBelgium	-1,025	,496	4,268	1	,039	,359
	DummySwitzerland	-,635	,439	2,088	1	,148	,530
	DummyCzech	-,949	,311	9,330	1	,002	,387
	DummySpain	-,781	,347	5,060	1	,024	,458
	DummyFrance	-,450	,342	1,736	1	,188	,638
	DummyItaly	-,841	,333	6,403	1	,011	,431
	DummyPoland	-,772	,346	4,988	1	,026	,462
	DummyRomania	-1,023	,382	7,175	1	,007	,359
	DummyUK	,071	,360	,039	1	,844	1,073
	DummyTurkey	-,946	,363	6,779	1	,009	,388
	DummyPortugal	-,168	,532	,100	1	,752	,845
	DummyNetherlands	-,808	,426	3,598	1	,058	,446

DummyIreland	-1,277	,631	4,091	1	,043	,279
DummyDenmark	-,257	,524	,241	1	,623	,773
DummyCyprus	-1,199	,876	1,871	1	,171	,302
DummyBulgaria	1,303	,669	3,793	1	,051	3,680
DummySlovakia	-,301	,568	,281	1	,596	,740
DummyLithuania	1,008	1,100	,840	1	,360	2,740
DummyGreece	-,979	,498	3,855	1	,050	,376
DummyEstonia	-,673	,800	,707	1	,401	,510
DummyAustria	,770	,531	2,098	1	,147	2,159
DummyHungary	-1,684	,440	14,658	1	,000	,186
DummySweden	,527	,703	,561	1	,454	1,693
DummyFinland	-,314	,619	,258	1	,612	,730
DummyNorway	-,265	,608	,190	1	,663	,767
DummyLuxembourg	19,957	27826,307	,000	1	,999	4,645E8
DummyMalta	,431	1,147	,142	1	,707	1,539
DummySlovenia	,285	,858	,110	1	,740	1,329
DummyLatvia	,209	1,166	,032	1	,858	1,232
DummyIceland	-1,429	1,149	1,546	1	,214	,240
SizeLog	,002	,078	,000	1	,984	1,002
SpecializationLog	,648	,110	34,846	1	,000	1,911
FocusLog	,221	,059	14,032	1	,000	1,247
Constant	,512	,308	2,767	1	,096	1,669

Appendix 10

Model 7

PLUM – Ordinal Logistic Regression

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1069,359			
Final	833,260	236,099	33	,000

Link function: Complementary Log-log.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	485,070	213	,000
Deviance	524,402	213	,000

Link function: Complementary Log-log.

Pseudo R-Square

Cox and Snell	,123
Nagelkerke	,140
McFadden	,063

Link function: Complementary Log-log.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Export = 1]	-1,347	,536	6,321	1	,012	-2,397	-,297
	[Export = 2]	-,044	,535	,007	1	,934	-1,092	1,004
Location	[DummyBelgium=0]	-,428	,241	3,143	1	,076	-,901	,045
	[DummyBelgium=1]	0[a]	.	.	0	.	.	.
	[DummySwitzerland=0]	,442	,230	3,686	1	,055	-,009	,892
	[DummySwitzerland=1]	0[a]	.	.	0	.	.	.

[DummyCzech=0]	-,500	,126	15,761	1	,000	-,746	-,253
[DummyCzech=1]	0[a]	.	.	0	.	.	.
[DummySpain=0]	-,245	,147	2,781	1	,095	-,534	,043
[DummySpain=1]	0[a]	.	.	0	.	.	.
[DummyFrance=0]	-,361	,144	6,241	1	,012	-,643	-,078
[DummyFrance=1]	0[a]	.	.	0	.	.	.
[DummyItaly=0]	-,212	,137	2,383	1	,123	-,482	,057
[DummyItaly=1]	0[a]	.	.	0	.	.	.
[DummyPoland=0]	-,254	,150	2,867	1	,090	-,549	,040
[DummyPoland=1]	0[a]	.	.	0	.	.	.
[DummyRomania=0]	-,183	,180	1,042	1	,307	-,535	,169
[DummyRomania=1]	0[a]	.	.	0	.	.	.
[DummyUK=0]	,153	,152	1,003	1	,317	-,146	,451
[DummyUK=1]	0[a]	.	.	0	.	.	.
[DummyTurkey=0]	,007	,166	,002	1	,966	-,317	,332
[DummyTurkey=1]	0[a]	.	.	0	.	.	.
[DummyPortugal=0]	,380	,269	1,998	1	,158	-,147	,907
[DummyPortugal=1]	0[a]	.	.	0	.	.	.
[DummyNetherlands=1]	0[a]	.	.	0	.	.	.
[DummyIreland=0]	,252	,347	,525	1	,469	-,429	,933
[DummyIreland=1]	0[a]	.	.	0	.	.	.
[DummyDenmark=0]	,151	,264	,327	1	,567	-,367	,669
[DummyDenmark=1]	0[a]	.	.	0	.	.	.
[DummyCyprus=1]	-,654	,546	1,433	1	,231	-1,724	,417
[DummyCyprus=2]	0[a]	.	.	0	.	.	.
[DummyBulgaria=0]	,476	,229	4,326	1	,038	,027	,924
[DummyBulgaria=1]	0[a]	.	.	0	.	.	.
[DummySlovakia=0]	,445	,298	2,237	1	,135	-,138	1,029
[DummySlovakia=1]	0[a]	.	.	0	.	.	.
[DummyLithuania=0]	,412	,445	,855	1	,355	-,461	1,285
[DummyLithuania=1]	0[a]	.	.	0	.	.	.
[DummyGreece=0]	,021	,254	,007	1	,936	-,477	,518
[DummyGreece=1]	0[a]	.	.	0	.	.	.
[DummyEstonia=0]	,114	,430	,071	1	,791	-,729	,957
[DummyEstonia=1]	0[a]	.	.	0	.	.	.

[DummyAustria=0]	,048	,205	,054	1	,816	-,354	,450
[DummyAustria=1]	0[a]	.	.	0	.	.	.
[DummyHungary=0]	-,213	,209	1,030	1	,310	-,623	,198
[DummyHungary=1]	0[a]	.	.	0	.	.	.
[DummySweden=0]	-,236	,288	,672	1	,412	-,800	,328
[DummySweden=1]	0[a]	.	.	0	.	.	.
[DummyFinland=0]	,693	,360	3,710	1	,054	-,012	1,398
[DummyFinland=1]	0[a]	.	.	0	.	.	.
[DummyNorway=0]	1,305	,405	10,376	1	,001	,511	2,099
[DummyNorway=1]	0[a]	.	.	0	.	.	.
[DummyLuxembourg=0]	,908	1,040	,763	1	,382	-1,130	2,947
[DummyLuxembourg=1]	0[a]	.	.	0	.	.	.
[DummyMalta=0]	,852	,587	2,109	1	,146	-,298	2,003
[DummyMalta=1]	0[a]	.	.	0	.	.	.
[DummyLatvia=0]	1,089	,699	2,431	1	,119	-,280	2,458
[DummyLatvia=1]	0[a]	.	.	0	.	.	.
[DummySlovenia=0]	,006	,412	,000	1	,989	-,802	,813
[DummySlovenia=1]	0[a]	.	.	0	.	.	.
[DummyGermany=0]	0[a]	.	.	0	.	.	.
[DummyGermany=1]	0[a]	.	.	0	.	.	.
[DummyIceland=0]	,422	,656	,414	1	,520	-,863	1,707
[DummyIceland=1]	0[a]	.	.	0	.	.	.
[Dummy1=0]	,639	,201	10,135	1	,001	,246	1,032
[Dummy1=1]	0[a]	.	.	0	.	.	.
[Dummy2=0]	,766	,219	12,288	1	,000	,338	1,194
[Dummy2=1]	0[a]	.	.	0	.	.	.
[Stars=1]	,915	,123	55,584	1	,000	,674	1,155
[Stars=2]	,294	,064	20,936	1	,000	,168	,421
[Stars=3]	0[a]	.	.	0	.	.	.

Link function: Complementary Log-log.

a. This parameter is set to zero because it is redundant.
b. For Dummies in this model: 0=yes 1=no
c. For Stars: 1=3 stars 2=2stars 3=1star

Appendix 11

Model 8

PLUM - Ordinal Logistic Regression

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	3768,333			
Final	3548,966	219,367	34	,000

Link function: Complementary Log-log.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	3636,859	3550	,151
Deviance	3548,966	3550	,502

Link function: Complementary Log-log.

Pseudo R-Square

Cox and Snell	,115
Nagelkerke	,131
McFadden	,058

Link function: Complementary Log-log.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Export = 1]	-1,080	,543	3,952	1	,047	-2,144	-,015
	[Export = 2]	,213	,542	,154	1	,695	-,850	1,276
Location	Size	,048	,034	1,967	1	,161	-,019	,114

Specialisation	,085	,018	21,161	1	,000	,049	,121
Focus	,033	,015	4,562	1	,033	,003	,063
[DummyBelgium=0]	-,417	,241	2,984	1	,084	-,890	,056
[DummyBelgium=1]	0[a]	.	.	0	.	.	.
[DummySwitzerland=0]	,427	,230	3,442	1	,064	-,024	,877
[DummySwitzerland=1]	0[a]	.	.	0	.	.	.
[DummyCzech=0]	-,492	,127	15,070	1	,000	-,740	-,243
[DummyCzech=1]	0[a]	.	.	0	.	.	.
[DummySpain=0]	-,281	,147	3,647	1	,056	-,570	,007
[DummySpain=1]	0[a]	.	.	0	.	.	.
[DummyFrance=0]	-,403	,145	7,772	1	,005	-,687	-,120
[DummyFrance=1]	0[a]	.	.	0	.	.	.
[DummyItaly=0]	-,237	,139	2,923	1	,087	-,509	,035
[DummyItaly=1]	0[a]	.	.	0	.	.	.
[DummyPoland=0]	-,296	,152	3,780	1	,052	-,594	,002
[DummyPoland=1]	0[a]	.	.	0	.	.	.
[DummyRomania=0]	-,045	,179	,062	1	,804	-,396	,307
[DummyRomania=1]	0[a]	.	.	0	.	.	.
[DummyUK=0]	,135	,154	,762	1	,383	-,168	,437
[DummyUK=1]	0[a]	.	.	0	.	.	.
[DummyTurkey=0]	-,047	,167	,078	1	,780	-,374	,280
[DummyTurkey=1]	0[a]	.	.	0	.	.	.
[DummyPortugal=0]	,337	,268	1,573	1	,210	-,189	,862
[DummyPortugal=1]	0[a]	.	.	0	.	.	.
[DummyNetherlands=1]	0[a]	.	.	0	.	.	.
[DummyIreland=0]	,265	,348	,581	1	,446	-,416	,946
[DummyIreland=1]	0[a]	.	.	0	.	.	.
[DummyDenmark=0]	,156	,265	,345	1	,557	-,364	,675
[DummyDenmark=1]	0[a]	.	.	0	.	.	.
[DummyCyprus=1]	-,562	,551	1,042	1	,307	-1,642	,518
[DummyCyprus=2]	0[a]	.	.	0	.	.	.
[DummyBulgaria=0]	,408	,230	3,159	1	,075	-,042	,859
[DummyBulgaria=1]	0[a]	.	.	0	.	.	.
[DummySlovakia=0]	,404	,299	1,832	1	,176	-,181	,989
[DummySlovakia=1]	0[a]	.	.	0	.	.	.

[DummyLithuania=0]	,554	,437	1,607	1	,205	-,302	1,409
[DummyLithuania=1]	0[a]	.	.	0	.	.	.
[DummyGreece=0]	-,038	,253	,023	1	,880	-,535	,459
[DummyGreece=1]	0[a]	.	.	0	.	.	.
[DummyEstonia=0]	,030	,432	,005	1	,945	-,816	,876
[DummyEstonia=1]	0[a]	.	.	0	.	.	.
[DummyAustria=0]	-,004	,207	,000	1	,984	-,409	,401
[DummyAustria=1]	0[a]	.	.	0	.	.	.
[DummyHungary=0]	-,285	,210	1,836	1	,175	-,697	,127
[DummyHungary=1]	0[a]	.	.	0	.	.	.
[DummySweden=0]	-,233	,288	,654	1	,419	-,797	,331
[DummySweden=1]	0[a]	.	.	0	.	.	.
[DummyFinland=0]	,689	,359	3,681	1	,055	-,015	1,393
[DummyFinland=1]	0[a]	.	.	0	.	.	.
[DummyNorway=0]	1,139	,403	8,006	1	,005	,350	1,928
[DummyNorway=1]	0[a]	.	.	0	.	.	.
[DummyLuxembourg=0]	,770	1,039	,549	1	,459	-1,267	2,808
[DummyLuxembourg=1]	0[a]	.	.	0	.	.	.
[DummyMalta=0]	,783	,589	1,770	1	,183	-,370	1,937
[DummyMalta=1]	0[a]	.	.	0	.	.	.
[DummyLatvia=0]	,988	,698	2,000	1	,157	-,381	2,357
[DummyLatvia=1]	0[a]	.	.	0	.	.	.
[DummySlovenia=0]	,171	,411	,174	1	,677	-,635	,977
[DummySlovenia=1]	0[a]	.	.	0	.	.	.
[DummyGermany=0]	0[a]	.	.	0	.	.	.
[DummyGermany=1]	0[a]	.	.	0	.	.	.
[DummyIceland=0]	,066	,672	,010	1	,922	-1,251	1,382
[DummyIceland=1]	0[a]	.	.	0	.	.	.
[Dummy1=0]	,761	,197	14,923	1	,000	,375	1,147
[Dummy1=1]	0[a]	.	.	0	.	.	.
[Dummy2=0]	,760	,219	12,026	1	,001	,330	1,189
[Dummy2=1]	0[a]	.	.	0	.	.	.

Link function: Complementary Log-log. (a) This parameter is set to zero because it is redundant.

For dummies:0=yes 1=no