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Modelling Innovative Business Clusters

A dissertation submitted by:

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To Walaa, Eleen and Ahmad with love.

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ABSTRACT

Science and Technology Parks (STPs) are often used as tools to foster regional development. They encourage innovation amongst the constituent firms, including by networking and knowledge spillover between the inhabitants and other actors. The high failure rate of STPs led us to evaluate a case study using panel data analysis as well as simulate how STP architecture can best cope with a changing innovation environment.

Data from the Ratsit database was obtained for firms in industry sector 62X (IT and related industry) in Linköping, Sweden and then divided into those on-cluster or off-cluster. Inhabitancy conferred protection for on-cluster firms against externalities. Longitudinal studies showed that micro-firms entering the STP exodus point was seen around 15-17 years when firms, grown to around 150 employees, either plateau out in growth or depart the locality. Size and age influence corporate turnover, as does the ability to innovate, but whereas size and age have a quadratic (non-linear) impact on financial growth, innovation capabilities have a positive linear impact. Employment is mainly correlated to age, previous years' innovation and shareholder investment. Innovation output is correlated to networking measured as social expenditure, which in turn exhibits a positive influence on innovation capabilities.

From the point of view of the host cluster, we simulated three organizational topologies for STPs; firstly, in the star model all are connected to the cluster initiative (CI), secondly the strongly connected model, when all are connected to each other, and finally the randomly connected model, where the network follows no centralised topology. Analyses used adjacency matrixes and Monte-Carlo simulation, trading transaction (networking) costs against knowledge benefit. Results show that star topology is the most efficient form from the cost perspective. Later, when the cost of knowledge transformation is lowered, then the strongly connected model becomes the most efficient topology.

Then, Agency-based Monte-Carlo simulations were then applied to clusters organisation to understand the impact of managers quality on innovation distribution using both poor and good innovation. Results show that it is very beneficial to have a central Cluster Initiative (CI) controlling the decision-making process in the early stages of STP development. However, with early maturity and commitment to a high-growth trajectory, high quality of decision–making is required amongst managers and decisions are best taken by the CI with the input of individual on-cluster firms. The scenario where CI is supported by good-quality decisions from on-cluster firms – an ambidextrous situation – is superior when good innovations abound and the STP has acquired a degree of maturity.

PUBLICATIONS ARISING FROM THIS WORK

Journal Papers

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Conference Papers

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Conference presentations and Posters

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Al-kfairy, M., Khaddaj, S. and Mellor, R. B. (2017) ‘Determination of Optimal Topology of Business Clusters Using Computer Modelling’. In: 12th European Conference on Innovation and Entrepreneurship (ECIE 2017). 21-22 Sept 2017, Novancia Business School Paris France.

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Abbreviations

ANOVA	Analysis of Variance
ANP	Analytic Network Process
CI	Cluster Initiative
EU	European Union
F-Level	Firms in Cluster, but not CI
GEM	Grounding, Enterprise and Market
Gov.	Government
HEI	Higher Education institutes
IASP	International Association of Science Parks and Areas of Innovations
IC	Integrated Circuits
ICT	Information and Communication Technologies
Innov	Innovation
KSEK	Thousands Swedish Korona
MNC	Multi-National Corporation
MSP	Mjärdevi Science Park

MU	Monetary Unit
NOE	Number Of Employees
NOF	Number of Firms
OLS	Ordinary Least Square
P&L	Patents and Licenses
R&D	Research and Development
R&DS	Research and Development Score
SC	Shareholders Contributions
SE	Social Expenses
SES	Social Expenses Score
SME	Small and Medium Enterprises
SMIL	The Foundation for the Development of Small Businesses in Linköping
S-O	Spin Offs
STP	Science and Technology Park
TC	Transaction Cost
TPV	Total Patent Value

VC	Venture Capital

Glossary and Definitions

Innovation	This study uses the expression "innovation" in three ways, applied in the appropriate context. 1. The production of new innovations within a firm as measured by the production of new products and ideas. 2. The adoption of existant innovations from the environment or between firms (e.g. arising from formal and informal networks) 3. The collective innovation of a business cluster as an innovation factory, for shorthand purposes a cluster acquiring an innovative firm is regarded as acquiring an innovation.
Knowledge Acquisition Costs	The transaction costs incurred by knowledge adaptation, trust-building, and employees networking costs. Running costs like lease and utilities are presumed to be constant per unit and thus excluded
Social Expenditure	It may include employees' activities (e.g. parties), inter-firms activities (e.g. partnership agreements cost), networking activities, team-building away-days and similar activities
Success	Is measured through several indicators including turnover growth, innovation growth, employment growth and the number of firms growth, which may lead business cluster to survive.

Chapter 1: Introduction

With intensified competition and globalization; where the competition shifted from comparative advantage into competitive advantage and distance, transportation cost and natural resources no longer play a crucial role in regional development (Porter, 1998), national and regional Governments are increasingly hoping on being able to create value by means of specific “knowledge ecosystems”. These ecosystems, together with business incubators and venture capitals, should be able to connect a reputable science-based with advanced knowledge, to business and finance in order to foster business clusters, which are called “Business Clusters”.

Generally, there are three types of industrial clusters. First, “pure agglomeration industrial districts”, which mainly contains a set of firms located in close proximity that support free labour movement between firms and considered as the primary source of knowledge sharing. The strategic reason for such cluster is to reduce transaction cost and the availability of specialised labour. This form of business clusters assumes no cooperation between firms, which may mean open rented office spaces only and does not follow any organisational structure, which impact cluster innovation output. Second, “industrial complex model”, which is characterised by supply and demand or industry and complementary relationships between different firms. It is major purpose to reduce transportation costs, by locating next to the input industry firms. The main issue of this model is “lock-in” due to the cluster structure inflexibility and adaptation of new knowledge. Finally, “social network clusters” that is established as a network structure between individuals and firms (formal or informal) as well as with institution. It enhances trust between firms, which encourages cooperative work between different firms even “risky investments”, which may reshape the cluster organisation structure (Gordon and McCann, 2000; Kolehmainen, 2002; McCann et al., 2002).

Another approach to distinguish between business clusters is based on the establishment methods, which are “top-down” when business cluster initiative is led by local authorities, government or regional development programmes. Or, a business cluster may be established by a set of interconnected firms (“bottom-up” approach). Therefore, the top-down approach is usually supported, funded and managed by governments institution, while conversely, the bottom-up approach is mainly a privately held investment, which organised and managed by constituent firms. The aim of the two approaches is to facilitate and encourage innovative activities which should result in beneficial innovation for inhabited firms (Fromhold-Eisebith and Eisebith, 2005; Jungwirth and Müller, 2014).

The different types of business clusters, as well as the approaches for building business cluster led into distinguishing between clusters, aims at providing office spaces, pure agglomeration and clusters which are more innovation-focused. This study investigates innovation business clusters and mainly Science and Technology Parks. Therefore, table 1.1 summarises the most well-known and agreed definitions of innovation business cluster.

Table 1.1 Business Clusters Definitions

Source	Definition
(Porter and Porter, 1998)	*Collection (set) of connected (through cluster initiative or partnership agreements...etc.) firms working in same or related industries and a specialized institution.*
(Morosini, 2004)	“*a socioeconomic entity characterized by a social community of people and a population of economic agents localized in close proximity in a specific geographic region*”
(DTI, 2004)	“*Groups of inter-related industries. They have two key elements. Firstly, firms in the cluster must be linked. Secondly, groups of inter-linked companies locate in close proximity to one other*”
(IASP, 2016)	*“A science park is an organisation managed by specialised professionals, whose main aim is to increase the wealth of its community by promoting the culture of innovation and the competitiveness of its associated businesses and knowledge-based institutions. To enable these goals to be met, a Science Park stimulates and manages the flow of knowledge and technology amongst universities, R&D institutions, companies and markets …”*
(UNESCO, 2017)	*“The term "science and technology park" encompasses any kind of high-tech cluster such as: technopolis, science park, science city, cyber park, hi tech (industrial) park, innovation centre, R&D park, university research park, research and technology park, science and technology park, science city, science town, technology park, technology incubator, technology park, technopark, technopole and technology business incubator…”*

Table 1.1 presents a variety of definitions for business clusters, which agree only on a few characteristics which are “connected firms”, connection with Higher Education Institutes (HEI) and R&D development. Connected firms and companies appear to be the foundation of business clusters. However, although there are different names of business clusters, they are all broadly similar, for example (Hobbs et al., 2017) argued that:

“ *... the term science park was more prevalent in Europe, the term technology park was more prevalent in Asia, and the term research park was more prevalent in the USA. That generalization has changed over the last decade. Today, it seems that the descriptive terms science, research, and technology are less of a label to describe the activities that occur on the park and more of a label to distinguish one park from another, especially if the other park is geographically close. What has remained relatively constant over time, however, is that most parks, regardless of location, are associated with a university*.”

Previous and successful examples include Silicon Valley, Silicon Fen, Silicon Corridor, Silicon Roundabout, Route 128 and similar (Moore et al., 2004; Saxenian, 1994) encourage regional and government bodies to support such initiative all over the world. For example, in Europe, there are more than 365 Science and Technology Parks (STPs) employing around 750,000, and with total investment of €12 billion, with the EU set of objectives to build innovation eco-systems to move away from declining industries and add important dimension into the smart specialization strategy (EU Commission, 2014).

The developed hypothesises suggested that clusters deliver essential benefits for both its surrounding regions and inhabited firms. Among others, improving regional employability level, as well as regional wealth, attracting investors and talents are some of the regional benefit, while clearly different types of firms can benefit differently from co-locating in a business cluster (McCann and Folta, 2011), but there is general agreement that inhabitancy can bring more benefits to SMEs [see (Sureephong et al., 2007; Maskell, 2001; Iammarino and McCann, 2006; Miao, 2017)] .

However, recent reviews of business cluster literature reveal the ambiguity in the role of the business cluster, with non-conclusive results. For example, some research reported no difference between locating on- and off-cluster (business clusters do not benefit its firms), while others suggested that off-cluster firms perform better. On the other hand, some concluded that being on-park helps firms to produce/invest more in innovation (NG et al., 2019; Ramírez-Alesón and Fernández-Olmos, 2017; Lamperti et al., 2015; Guadix et al., 2016), for recent reviews of business cluster literature [see Lecluyse et al., 2019; Hobbs et al., 2017]. Therefore, researchers studied business clusters from different perspectives to identify business clusters success factors and Lecluyse et al. (2019) summarised that business cluster (Science and Technology Parks (STPs)) studies could be categorised into three different types based on its research objectives. First, research which focuses on the contribution of a business cluster at both regional and micro-level. Second, studies which focus on location impact of firms, and science parks impact on its region. Third, researches which focus on cluster networking structure and impact of networking with other cluster actors on innovation performance such as networking with Higher Education Institutions (HEI), and Cluster Initiatives (CIs). Thus, this study aims to conduct a comprehensive study using a top-down approach by first analysing the business clusters contribution into its inhabited firms, followed by identifying business cluster success factors, then analyse how these factors are connected to the organisation theory. Next section highlights the main research objectives and contribution, then identify thesis structure.

1.1 Research aim, background and contributions

1.1.1 Aim

The aim of this thesis is to uncover business cluster contribution into its inhabited firms using a data-driven approach and Mjärdevi Science Park (MSP) case study. Then using panel data analysis to extract business clusters' success indicators which leads into finding the set of business cluster success factors. After that, we used Monte-Carlo simulation to find the best business cluster organisational structure at different development stages of the business cluster. To elucidate:

1. Do "on-cluster" firms experience advantages over "off cluster" firms? and given that the answer to the above is a highly-qualified "yes";
2. What is the best corporate structure for a small "bottom-up" STP and how does that develop through an expansion phase into early maturity?

Next section discusses the research background, problem and questions.

1.1.2 Background and research questions

This thesis builds on previous literature suggesting that locating in business cluster benefits is uncertain, meaning that building STP does not guarantee success for its inhabitants (Lecluyse et al., 2019; Hobbs et al., 2017). For example, the success rate in Wales was 40% (BBC, 2010; Pugh et al., 2018), a cost to the UK taxpayer of many millions [BBC estimated it to be 100 million]. However, there is a belief that they are the main factory of innovation when compared to off-cluster firms (Porter, 2003). This suggests that the nature of success is not the location itself, but instead, what is available in that specific location. Therefore, scholars shifted their attention from benefit studies into identifying the success factors, which focuses on business cluster organisation, knowledge spillover, and characteristics. For example, NG et al. (2019) show that business clusters landscape presents a variety of types. Those types can be distinguished based on cluster size, presence of HEIs, organisation and cooperation network types that shapes the different collaboration networks in order to foster more innovation. Thus, business clusters foster the regional innovation systems (Cooke et al,1997) with different actors consisting of Cluster Initiative (CI), HEIs, R&D institutions, private support and government support (triple-helix view of the regional system).

Based on the type of collaboration and owner of business clusters, some can be young, and others can be mature. Young clusters can be massive, which depends on the amount of investment (private or public) and the approach employed (top-down or bottom-up) (Skokan et al., 2012). In this case, CI managers face a set of immediate problems like how to collect sufficient rent to survive. One could imagine that to generate additional income; clients are rapidly recruited that are active in various fields. It is known that on-cluster firms select working partners from various sources like HEIs (Johnston and Huggins, 2018), so it is difficult to imagine how synergy ("local buzz") can be constructed if the themes present in the STP are unrelated (Bathelt et al., 2004).

Networks are known to be of prime importance in creating innovation systems (Morosini, 2004; Pitelis, 2012; Mellor, 2015; Tavassoli and Tsagdis, 2014) and thus start-up STPs can grow (Skokan et al., 2012) as a coherent whole. However, there are significant differences between the "baby-boomer" STPs and the "Post-Millennial" STPs. Nowadays, the innovation environment is much more tightly packed. Even a casual glance at software supposedly enhancing one's office work will generate a large number of returns, implementing innovations that are unsuitable for an organisation, e.g. too expensive for the company to realise or not in alignment with core competencies etc, will be very harmful.

One of the new aspects used here is the concept of "poor innovations". Mellor (2019) points out that the value (I) of implementing a useful innovation is I-C where C represents the costs of implementation. For a poor innovation the loss is greater, -(I+C). Will et al (2019) show this graphically (figure 1.1).

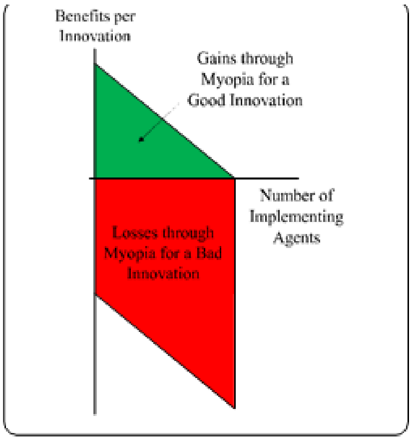
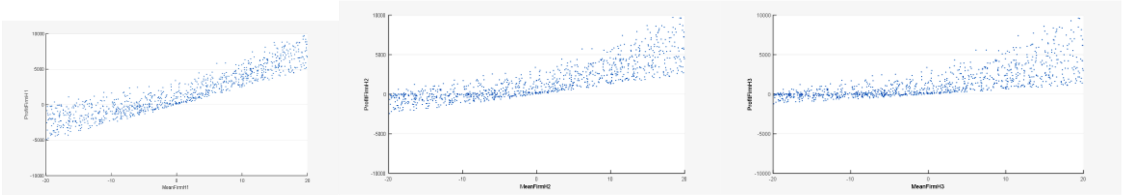


Figure 1.1 Gain and loss in case of innovation with spillover effect green triangle: myopia in the case of a good innovation; red quadrilateral: myopia (in the case of a bad innovation).

In environments that contain many "bad" innovations; fads and fashions can circulate unchecked and these bad ideas can swarm into the workplace and resemble epidemics swirling in waves across the workforce, harming the organisation. To this scenario, let us now add the simplest form of hierarchy, one manager and furthermore let us assume that this manager makes decisions about implementing innovations by flipping a coin. In the case of a firm with this hierarchy, the loss is halved compared to the flat organisation (figure 1.2).



Incremental Innovations Hierarchy (1 Level Hierarchy)

Incremental Innovations Hierarchy (2 Level Hierarchy)

Incremental Innovations Hierarchy (3 Level Hierarchy)

Figure 1.2 Plots of the effect of incremental innovations on organisation performance in polyarchies and hierarchical organisations.

Thus, possibly in large new STPs, and in small STPs in environments with poor innovations, client firms will tend towards favouring "bad" innovations and in these situations having a hierarchy (CI) containing managers making random decisions is still enormously better than having no hierarchy at all (although clearly an STP with coin-flipping managers will lose out on beneficial innovations in the long run). Indeed, computer models (Mellor, 2016; Mellor, 2018) have surprisingly shown that the costs of poor management are not onerous.

However, if the "community" of client firms in an STP are well-aligned and coordinated with good judgement and communication, then useful innovations (including selecting new inhabitants that "fit") are chosen and benefits rapidly become apparent.

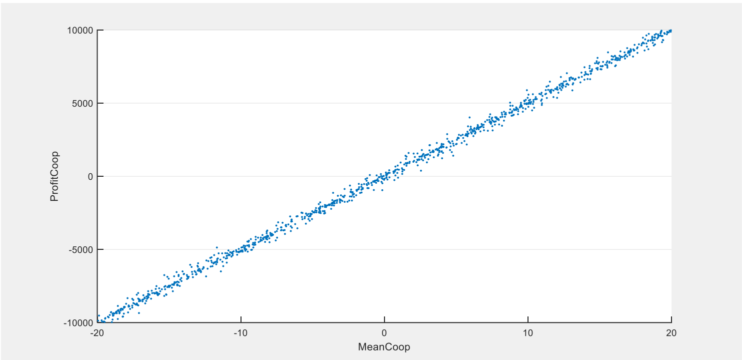


Figure 1.3 Incremental Innovations Polyarchy

Will et al. (2019) show that where a workforce of highly-skilled employees can discriminate between useful and harmful innovation with a high degree of accuracy, and managers have become facilitators, superior corporate performance can be expected, akin to the organisational structure attributed to, e.g. Google and other contemporary tech start-ups. The question is, can these principles be applied to STPs? To investigate this, we initially take a step back and investigate the following research questions:

1. Firstly, ask the question of how is being on-cluster advantageous, and how do inhabitant firms behave?
2. Secondly, we approach the STP structure from a transaction cost perspective to determine the risk-return trade-off of innovation and the tension between exploration and exploitation.
3. Thirdly, we model benefits and losses for "ambidextrous" STPs in different innovation environments. Nobel laureate Joseph Stiglitz showed that the organisational structure determines how innovations spread, so what dimensions of leadership are needed in STPs with various architectures, and how does this differ during developmental stages?

To do this, we use data collected for one of the most successful business clusters located in Sweden, namely Mjärdevi Science Park (MSP), multiple statistical models and Markov Chain Monte Carlo analysis. Because scatterplots are typically platykurtic, we developed a new regression analysis technique to achieve results that are more accurate than those published by others.

1.1.3 Contribution to knowledge

This thesis adds to the current understanding of the contribution of business clusters in the form of Science and Technology Parks to its inhabited firms. Using a well-established case study, results show that locating inside a business cluster will help firms spend more on R&D and networking activities which results in more innovation output in the form of patents licensing. Moreover we observe that financially, both on-cluster and off-cluster firms perform relatively good, however, on-cluster firms perform better up until the age of 15, then off-cluster firms start to perform better. On the other hand, results show that by locating on-cluster, there is a higher possibility that firms will grow from micro to medium size firm. These results prove the contribution of successful business clusters to its inhabited firms, which is a research debate. The results are further discussed in Chapter 4.

Then using the case study data, we evaluated three firms success indicators for firms located inside a business cluster, which are firms' innovation output, firms' financial performance using turnover growth as well as firms employment growth (size) (see figure 1.4). the analysis shows that business cluster firms' development is not linear. It indicates that firms growth is mainly impacted by firm age (not linear), and positively related to the innovation capabilities (chapter 5). Firms' networking impacts innovation output. However, firms' networking shapes the cluster organisation structure. Therefore, we studied cluster organisation structure using networking cost, innovation benefits (poor and beneficial innovation), and the quality of firms managers (gatekeepers) using Monte-Carlo simulation. The results show that it is vital to have a high-quality Cluster Initiative (CI) managers who evaluate incoming innovation project. This is especially the case at early stages of cluster development (chapters 6 and 7). Figure 1.4 summarises business cluster success indicators and factors as reported in the thesis. In conclusion, this research adds to the current knowledge by:

1. Identifying the role of business clusters for inhabited firms development and the performance difference between firms located inside a business cluster and outside the business cluster.

2. Extract a set of business clusters' success factors from the identified success indicators.

3. Understand the impact of business cluster organisation structure, type of innovation and quality of cluster and firms manager on innovation distribution and the benefits of the aggregate innovation outcome.

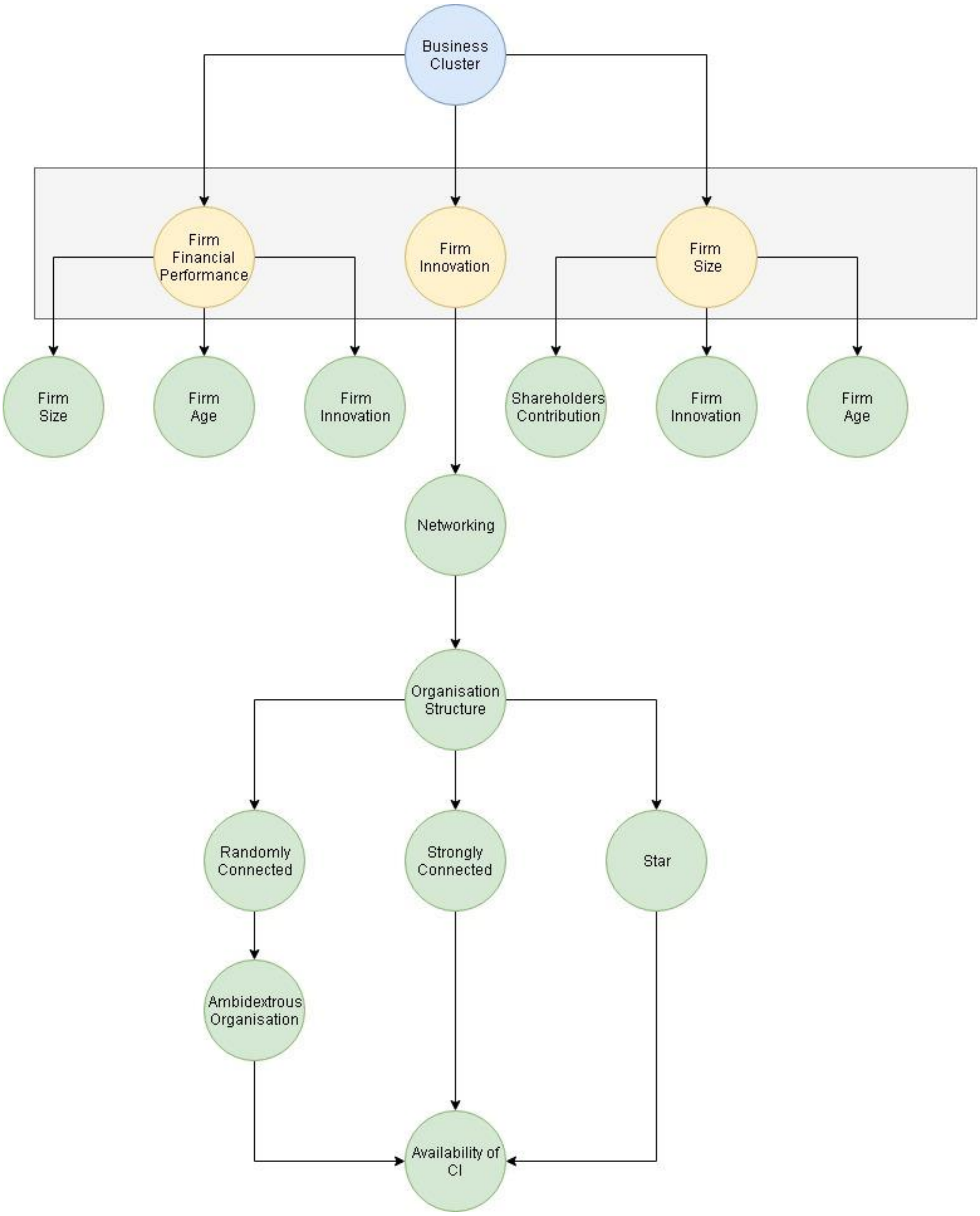


Figure 1.4 Overvirw of Business Clusters Success Indicators and Factors

1.2 Document organisation map

Table 1.2 shows how the thesis is organised, describing each of the chapters and its objectives and content.

Table 1.2 Document Organization

Chapter Name	Description
Literature Review	Discusses the business cluster eco-systems and the development stages business clusters' move through during its lifecycle. Then, it discusses how scholars assess the impact of a business cluster at both micro and regional levels.
Context, Data Source and Methods	Identifies the key research steps and methods used to reach the research objectives. It further discusses the case study, data sources and analysis methodologies.
The efficiency of Business Cluster	Compares on- and off-cluster firms to evaluate which group are performing better. It used to understand the actual contribution a successful business cluster brings into its region, and firms inhabited inside the business cluster.
Modelling Business Cluster Success Factors	Analyse the data at the aggregate level, and micro level, and empirically identify business clusters' success factors using identified indicators.
Simulation of Business Cluster Optimal Structure (topology)	Evaluating three networking structures of business clusters, including star topology, strongly connected model, and randomly connected model from both networking cost and benefits to find the best cluster topology and under which conditions.
Innovation Distribution Under Different Innovation Environment	Extending previous work to understand the impact of cluster firms' managers' quality on cluster innovation outcome, based on different structures identified in the previous chapter.
Thesis Conclusion	This chapter aims to conclude results obtained throughout this research and set a foundation for future researches.
Appendix 1	The appendix aims to present a sample of econometric models we tried to develop.

Next chapter discusses cluster theory starting from defining its ecosystem and lifecycle models.

Chapter 2: Literature Review

2.1 Introduction

The traditional Resource-Based View (RBV) of the firm arises from an industrial organisation approach that assumes there is a business reality about which information can be gathered and processed to arrive at rational decisions which are subsequently acted upon by management layers in order to realise the strategy involved. The RBV, however, has difficulty with the concept of fundamental innovation and change. These concepts are at the heart of the Knowledge-Based View (KBV), which is centred on a firm's dynamic capability. Unfortunately, there can be considerable confusion around what that is and how to acquire and develop it, which in turn forms the rich ups-and-downs playground of knowledge management theorists. The last 40 years have furthermore seen the rise of a view implying that concentrating knowledge-intensive innovative young firms together increases synergy even more. Originally these "clusters" were mostly spontaneous ("bottom-up") but in the last decades (since Porter's competitive advantage) business clusters, especially in the form of Science and Technology Parks (STPs) have received much attention from scholars, governments and local authorities as a tool for fostering innovation and regional development. Latterly, these pre-meditated initiatives are often funded with tax-payer money ("top-down") and firms self-select whether to become inhabitants ("on-cluster") or remain outside ("off-cluster"). Previous studies on business clusters are categorized into the following:

- Conceptualising business cluster development lifecycle, eco-system, networking structure [see (Martin and Sunley, 2011; Martin and Sunley, 2003; Padmore and Gibson, 1998; Ruiz et al., 2017)]. Such studies focus on how different components of business clusters are interacting with each other, how networking establishes the structure of business clusters and different development stages of business clusters. Other dimension includes studies focusing on the management bodies (CI). Understanding these studies help to identify the essential components of business clusters and how they are interacting with each other. Recent reviews suggested a name “mediator” studies of business clusters [see Lecluyse et al., 2019]. These concepts are discussed in sections 3 – 6 in this chapter.

- Evaluating business clusters’ efficiencies and their role in regional development, and often use off-cluster firms group as a control group [see (Ramírez-Alesón and Fernández-Olmos, 2017; Dettwiler et al., 2006)], they help identifying which parameters can be used for benchmarking business clusters (success indicators) that leads into identifying business clusters success factors, often called input-output studies (Lecluyse et al., 2019) (sections 2 and 7).

This chapter aims to understand the different perspectives of previous studies in order to identify the foundation of the thesis and the currently available knowledge. It starts by identifying business clusters advantages and disadvantages in the next section.

2.2 Advantages and disadvantages of business clusters

The main goal of building business clusters is to stimulate regional development and wealth and normally to act as innovation factory for its firms. There is a broad agreement that successful business clusters benefit both its region and firms (Porter, 1998; Porter, 2000). However, it is not guaranteed that business clusters are always advantageous. Thus, this section discusses both the advantages and disadvantages of business clusters.

Historically, business clusters were developed to reduce transportation cost between suppliers and buyers. They also tend to reduce transaction cost by simplifying the flow of information and knowledge between firms especially freely available knowledge (see 2.5) (Gordon and McCann, 2000; Kolehmainen, 2002; McCann et al., 2002). Business clusters reduced the hurdle in knowledge transformation by enabling different ways of knowledge transformation between its inhabited firms and the region. For example, the enhanced formal and informal network between firms enhances trust between the firms and consequently knowledge is seamlessly moving between the different firms through cooperation and partnership projects and/or free labour movement (see 2.5). In addition, locating inside a business cluster may save firms cost (another form of transaction costs) which includes, cost of infrastructure (freely available infrastructure), availability of "input-suppliers" and business services, and the availability of well-trained personnel who is ready to transfer their expertise and knowledge (reducing the training time), and availability of supporting institution (public and private) (Barkley and Henry, 1997; Cojocaru, A. and Ionescu, 2016).

Moving from micro-level into the regional level, business clusters are assumed to boost regional wealth, by increasing the employment level inside business clusters, encourage entrepreneurship inside the region through supporting programmes (e.g public fund and incubation programmes) (Wonglimpiyarat, 2016; De Fontenay, 2004). They furthermore help to attract MNCs into its region which improves the regional overall knowledge stock in specific industries resulting in more spin-offs and entrepreneurial activities as well as the international reputation of the regions (Saxenian, 2004). Moreover, business clusters may help policymakers to focus regions limited financial resources more efficiently by focusing on a more specialised industry, personnel development programmes and firms economic support programmes (Barkley and Henry, 1997).

On the other hand, business clusters may have some side effects, which can be summarised as: first, policymakers may misjudge and select the wrong targeted industry, which may result in investing a considerable amount of tax buyers building the wrong infrastructure and the wrong supportive programmes (Barkley and Henry, 1997; Sunley and Martin, 2010). Second, technology and regions are continuously changing over time, therefore, firms' absorptive capacity and cluster openness for new incumbent.

In some cases, when clusters are not open for new firms and firms are not reacting to economic changes, they will enter a lock-in stage, which is cited as one of the major reasons of business clusters failure (Barkley and Henry, 1997; Sunley and Martin, 2010; Breschi and Malerba, 2001; Tallman et al., 2004). Moreover, business clusters may provide competitive advantages for early cluster inhabitant through its supporting programmes (i.e rent and incubation help), however, when cluster gets older, and grow, the same benefit may be limited for the newcomers and some issues with office rented becomes higher, which becomes a hurdle for new start-ups (Barkley and Henry, 1997; Sunley and Martin, 2010). Other issues may include space availability and cluster expansion plans. Therefore, it is very important for policymakers and investors to pay attention to cluster development hurdles and problems when planning a new business cluster. Therefore, the next section will discuss the different business clusters evolvement mechanisms.

2.3 Cluster development

A convenient starting point for topological studies is that clusters can be top-down or bottom-up; the implications are given in Figure 2.1 and Figure 2.2.

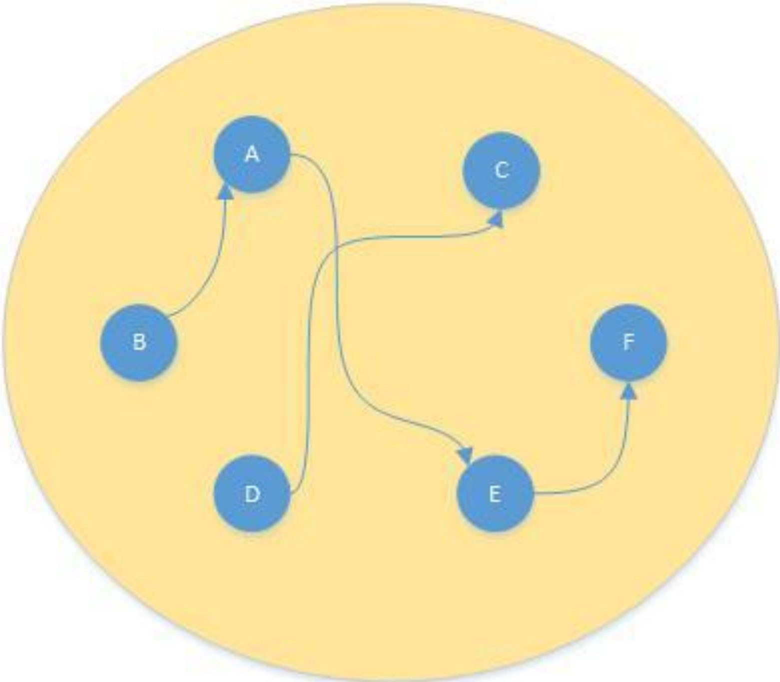


Figure 2.1 Critical Mass of Companies

Although it has been argued that different industries can have different topologies of business clusters and that topology can change over time, but they all share common characteristics which will be discussed in this section (He and Fallah, 2011). Some studies refer to business clusters as a “virtual enterprise” which follows – to some extent – the same organisation hierarchy of large firms and connect innovation similar to a large corporation (Lin et al., 2006). However, business clusters can be established either as a networking organisation among current firms, which is called “bottom-up” approach. Alternatively, it can be a result of government policies i.e. established by public/local authorities, which are called a “top-down” approach (Skokan et al., 2012). For example, Silicon Valley and Round 128 was a self-evolution example of business clusters (bottom-up approach), Linköping Science park was planned by Linköping city council at 1969 (top-down approach)[1](Saxenian, 1994; Bresnahan and Gambardella, 2004; Hommen et al., 2006). Recently, the bottom-up approach of business clusters in the form of STPs received extensive support from regional and local authorities as a way to stimulate regional development, especially to enhance knowledge-intensive industries[2].

The business clusters ecosystem contains typically different components. First, it contains several interconnected firms – which are the main building block of any business cluster - working in same or related industries. These firms are connected either through partnership agreements or cluster initiatives [see(Shakya, 2009)], spin-offs (when a company sell one of its division or create a branch of the parent company to produce new product and services, but they still have either direct or indirect – maybe both – connections with the parent company) or work in the same industry.

Second, a higher education institution (HEI) connected to the cluster which plays a vital role in the cluster development as either university spinoffs with what is called now "entrepreneurial universities" (De Silva and Mccomb, 2012; Smith and Bagchi-Sen, 2012) or through filling in the gap of industrial expertise needed (Davis et al., 2006). It is assumed to be a crucial source of knowledge, which enhances start-ups and stablished (mature) firms' innovation (Pique et al., 2018).

The third part is a government, public or private authority, which is - sometimes - called cluster initiative (CI). Cluster initiatives are defined as an intermediary

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[1] However, Linköping Science Park was not established until 1984 when companies started to move there.

[2] Check the list of EU Science Parks at http://www.unesco.org/new/en/natural-sciences/science-technology/university-industry-partnerships/science-parks-around-the-world/science-parks-in-europe/ and the list of IASP is available on https://www.iasp.ws/our-members/directory

organisation which is trying to help business clusters to grow thorough building a networking platform between firms, connecting firms and VCs and helping in building the right public policies by connecting firms and public (Klofsten et al., 2015). CIs normally contain an incubator as part of it, or it might be a different organisation which takes care of providing a space and business training for new start-ups. It fosters new ideas, helps to develop these ideas and provide the needed support for start-ups to grow (Herliana, 2015).

The importance of a central Cluster Initiative (CI) is widely acknowledged; this is the organisation that manages the STP and helps on-cluster firms to grow via providing a set of activities and support policies. The CI should provide a clear vision and measurable goals to identify the support required for each group of firms, as well as providing the resources required. It provides well-trained and organised managers who liaise with representatives within on-cluster firms to, e.g. facilitate and organise internal knowledge exchange workshops. Ruiz et al. (2017) added that CI management should provide both tangibles like connections to Venture Capitals (VCs), land management, offices management etc, as also intangibles like facilitating knowledge sharing and acquisition, opportunity hunting and liaison with governmental and other bodies to facilitate, e.g. future technology policies and direction.

The fourth core part of business clusters is what is called “Venture Capitals” (VCs). VC is – generally – a risky investment in early established or growing firms for helping them in developing “new” products or innovations aiming that this will pay back shortly (Black and Gilson, 1998). However, government support can act as a VCs, which supports firms in its early development through providing funds or accelerator programmes(Leydesdorff and Etzkowitz, 2003; Skokan et al., 2012; Grilli and Murtinu, 2014).

Figure 2.2 shows a simulated, established business cluster. This figure assumes that there is a central node in the cluster network, which is the CI as described above. The CI can be initiated by a group of already established SMEs or by local authorities.

The CI will connect different parts of the eco-systems. However, it is not necessarily that all SMEs are connected to the CI; some might not accept the partnership with CI. SMEs can connect either through partnership agreements, through CI, spinoffs or through being a child company of a parent. Some SMEs might be a spin-out of company research such as SME. VCs can find SMEs using CIs or can connect directly to SMEs. Figure 2.1 shows a normal topology which can be found in any cluster, there might be a presence of CI or not, higher education institutes or not, but in most of the cases, CI and higher education institutes will be there. Next Section discusses in details business clusters eco-system.

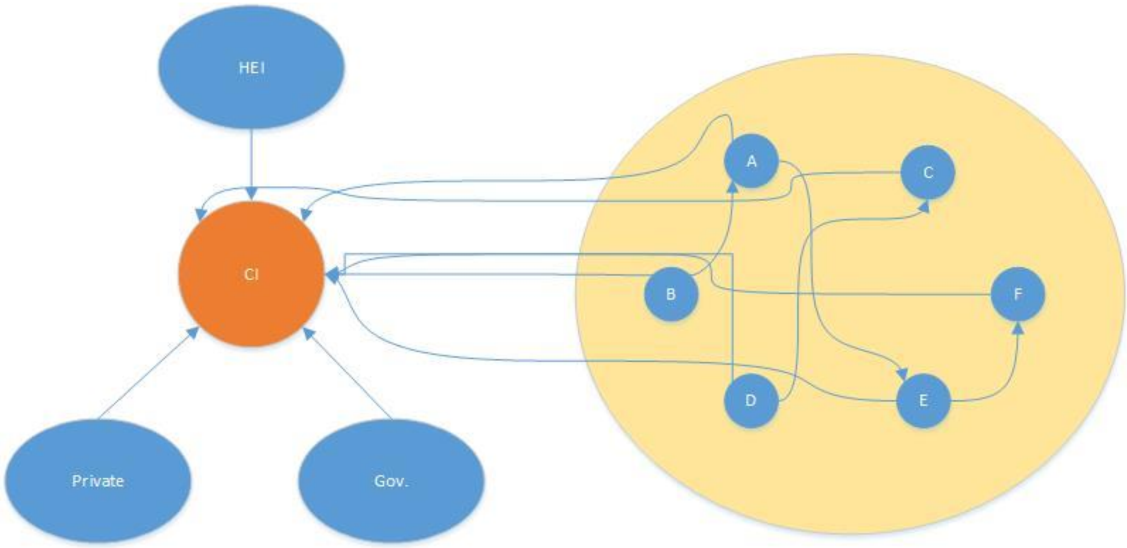

Figure 2.2 Business Clusters' Eco-system (Triple-Helix)

2.4 Business clusters structure and main actors

The purpose of this section is to summarise the role of each of business cluster actors in both supporting cluster development as well as innovation as defined in porter diamond, triple helix theory as well as previous conceptual, and empirical studies. Business cluster as innovation system should contain several actors/factors to prosper. Previous contributions on innovation systems suggest a number of system components including region, innovation, network, learning and interaction (Cooke, 2001). These components are connected in order for the whole system to work. The region needs a set of connected (networked) firms and institutes, with learning (absorbing) capabilities through interactions with HEI and R&D institutions, and continuous interactions. The networking structure and knowledge flow will shape the business clusters topology. Thus, NG et al. (2019) distinguished between different business clusters topologies bases on business clusters size, owners, and the availability of HEIs, a system which is similar to both Porter diamond and triple-helix theory. Then, this section starts by introducing Porter diamond, then the role of HEI, after that public and government role is discussed, followed by the crucial role VCs play, finally the role of the firms located inside business clusters.

2.4.1 Porter's diamond

Business cluster organisation normally contains different components, which interact with each other and form the knowledge spillover system. Two theories typify cluster organisation: Porter Diamond (Porter, 1998; Porter, 2000) and Triple helix theory (Leydesdorff and Etzkowitz, 2003; Skokan et al., 2012; Grilli and Murtinu, 2014), which is mainly dependent on how business cluster is established (top-down or bottom-up) (Figure 2.3). However, both theories are not independent of each other and can be combined to establish a good picture of cluster eco-system. Porter Diamond contains four components, which influence each other, but they are influenced by other triple helix components and vice versa.

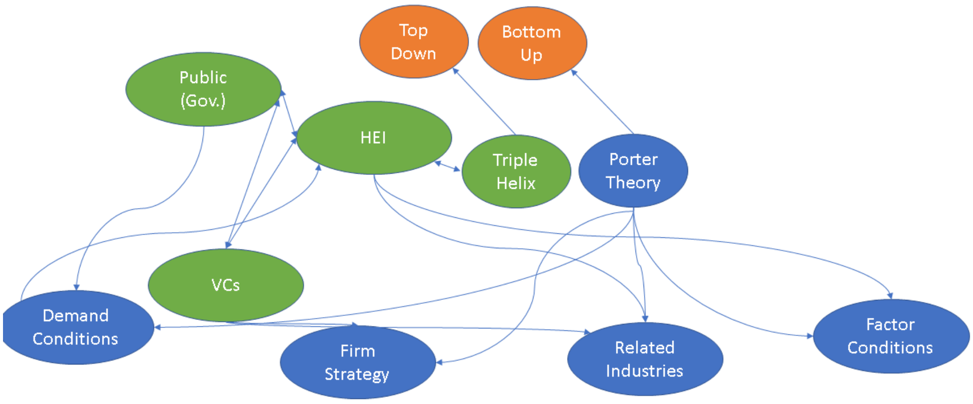

Figure 2.3 Business Clusters' Eco-system

Porter's cluster conceptual model is presented in Figure 2.4, which contains the following:

1. ***Factor conditions:*** are the needed input for the whole system to work. This includes skilled (needed) labour and knowledge availability (through universities institutes or local firms), which is an integral part of the triple helix theory, infrastructure as a government or private investment, natural resources and venture capitals. These factors can be divided into "basic factors" such as the availability of natural resources and "advanced factors" such as the availability of Information and Communication Technologies (ICT) infrastructure and very well-educated resources. Basic factors influence basic industries such as agriculture, while knowledge-intensive industries are mainly determined by advanced factors. The availability of basic factors will impact domestic competition and will create a home industry base. While advanced factors are shaped by the availability of domestic competition. For example, in

Denmark had 11 agriculture colleges in a 5 million country which was a result of the agriculture industry prosperity. In connection to Triple helix theory, this highlights the importance of HEI fuelling the regional flourished industry. On the other hand, they can be influenced by the related industries and suppliers once the education and knowledge are transferable such as the biological expertise in the Danish market resulted by focusing on the agricultural industry. The availability of factor conditions can also help in building a home industry. For example, the spinoffs resulted from the research institutes and labs or entrepreneurial universities as a result of growing expertise in the region, where knowledge spillover becomes dominant for that specific industry. While companies' strategy of moving into a newly emerged industry can be built upon – in some cases – research-based or, the new emerged industry will give attention to university programme builder to introduce new educational programs which may produce some spin-offs.

2. ***Demand conditions:*** the availability of home demand for a particular product, service or industry and the size of the demand. Home demands can foster more innovation by giving local firms indications on the buyers' needs. Open communication channels are needed in order to understand buyers' needs. Demands conditions usually are influenced by the power of local competition, which pressures local firms to innovate and give a better understanding of the industry. Related and supporting industries can enhance international demand of that specific industry, especially by gaining a reputation for the availability of the industry and related needed parts. As a result, this will help in factor creation when gaining a reputation of having a specialised industry by attracting foreign and local students and researchers who can – in future – fuel that industry with the needed resources, entrepreneurs and knowledge spillover (Porter, 1998; Porter, 2000). Home demand encourages entrepreneurial universities to build programmes which help meet the home needs. Typically, demand conditions impact all triple-helix components by putting pressure on local authorities (government) to

encourage entrepreneurship and investment in home industries, which results in industry prosperity.

3. ***Companies strategy and rivalry:*** which covers the companies and individual goals to compete internationally. It is targeting local demand as well as the innovation strategy implemented at the firms' level. However, this determinant is generally affected by national circumstances and policies. This determinant will influence the activities of the related and supporting industry by placing considerable pressure to support local innovation needs. On the other hand, it will stress factor creation not only for the industry needs but for other complementarities such as managerial educations and expertise and financial needs (Porter, 1998). Also, the company's strategy influenced by the available investment firms have in order to innovate, as typically innovation costs. This highlights the importance of VCs availability as part of the triple-helix theory. It is also influenced by the availability of knowledgeable labour to help to build the right strategy (as part of the factor creation process).

4. ***Availability of related industries and supplier:*** The presence of internationally recognised suppliers and related industries which help fuelling the nations domestic industry. This provides an efficient and fast way of accessing needed input. It fosters more innovation when good networking ties are available between suppliers and input. This is a two ways effect where both input industry and industry can affect each other. For example, the industry can place more pressure on the input to provide better and more efficient inputs or implement new methods to create better input. On the other hand, this can come first from the input industry. The availability of related inputs can affect all other determinants. For example, it can influence the way that managers build their plan if the specialised input suppliers are available at home, or they will need to communicate with international supplier. It can build a nation (cluster) reputation of the technology and industry availabilities in all levels (Porter, 1998). The need for input industry will also have an impact on all components of

the triple-helix theory, by encouraging HEI to build the right programmes and both government and privates to invest in the right industries.

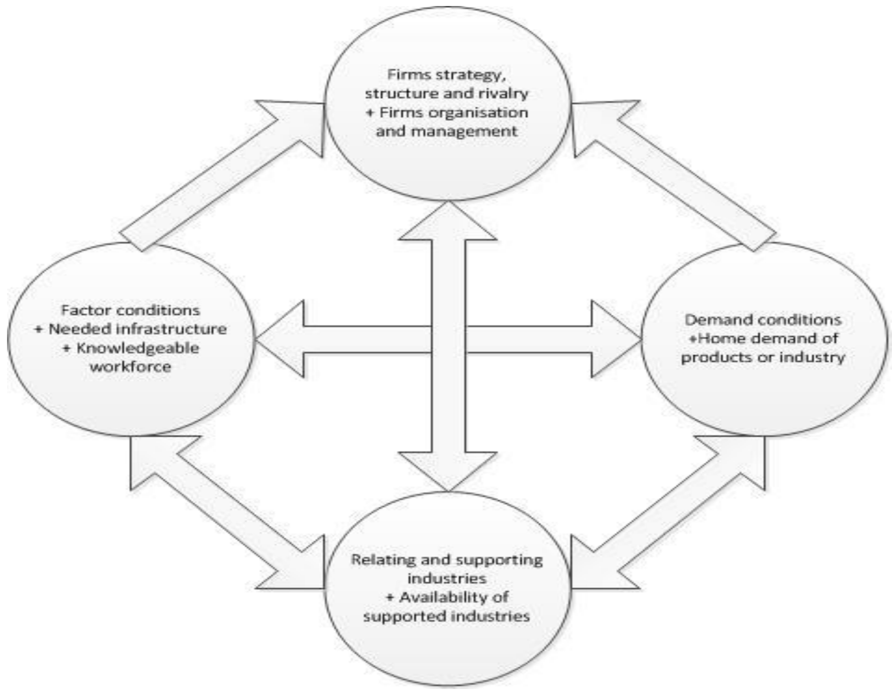

Figure 2.4 Porter's Diamond

Porter's diamond works as a networking system, where each determinant in the system can influence one or more determinants, and in most of the cases, it can influence the whole system. In some cases, the system can work in the absence of one determinant, such as the case of the thread industry in the UK by establishing remote production sites to substitute the disadvantage of high labour cost. However, there are many arguments about the diamond as a system. For example, Dunning (1993) highlighted the importance of multi-National Corporations (MNC) in maintaining competitive advantages. Moreover, he criticised that the diamond has omitted and underestimate the importance of international connections and cross border communication in building a sustainable competitive advantage through, e.g. Foreign Direct Investments (FDI), MNC connections and international partnership agreement which can enhance firms innovation or act as supplier/input for firms. Eickelpasch et al. (2007) reported a contradicting result to Porter´s assumption, implying a negative impact of internal competition on firms' performance and innovation when tested 2100 firms' sample in east Germany. However, they reported a strong correlation between firms' cooperation (networking) and firms' innovations and performance; while their findings highlighted the importance of related and supporting industries in stimulating more innovation and enhancing firms' performance. Furthermore, they highlight the negative impact of demand conditions on innovation and performance which is contradicting porters' assumption.

Previous paragraphs present the classical Porter view of the business clusters and show how each component can affect the others. It highlights the importance of this network in fostering more innovation and presented that Porters' diamond cannot – as is – present business cluster topology and how it works. Thus, the next section will take a closer look into the role of HEIs in sustaining business cluster development.

2.4.2 Higher Education Institutions (HEIs)

The classical role of research institutes and universities has been changed since the theory of Silicon Valley. For example, Stanford University and Cambridge University have played a crucial role in regional economic development. They are a very integrated part of Silicon Valley and Cambridge business cluster[3] (Moore et al., 2004). They are a very important component of the triple helix (it is reproduced in Figure 2.2) and business cluster model, and considered as one of the main actors in knowledge spillover between academia and business clusters (Figure 2.5) (Etzkowitz and Leydesdorff, 2000; Leydesdorff and Etzkowitz, 2003; Markkula and Kune, 2015). The following paragraphs outline the role of HEI in business clusters development.

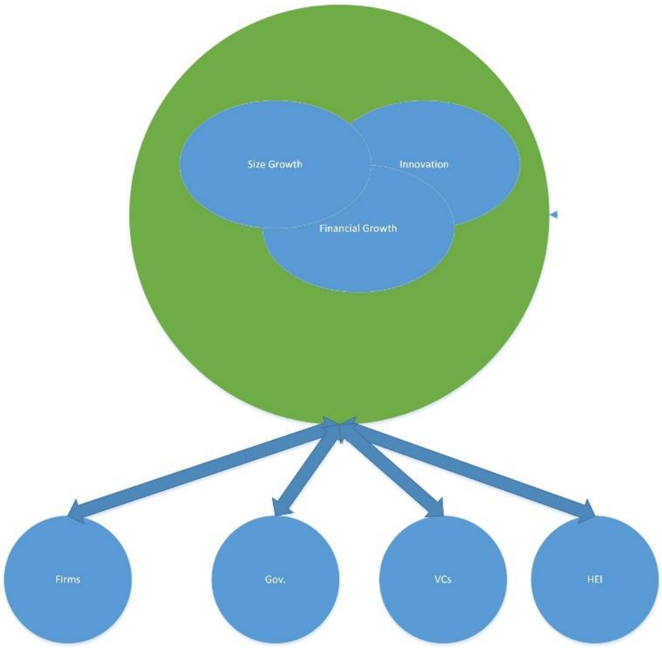

Figure 2.5 Business Cluster Actors

Deliver knowledge and provide the surrounding regions with the needed skills. First of all, universities should deliver the needed knowledge into its surrounding regions (ECOTEC, 2003), which is very important in building the right pool of skilled

[3] Sometimes referred as Silicon Fen

labour, which is considered as a very important factor, while labour shortage is a declining reason (Davis et al., 2006). For example, in India and mainly in Bangalore area, research institutes were providing the right essential “critical mass”, which was used to fill in the demands for the emerged development in the ICT sector (Arora et al., 2004).

Commercialisation/productisation of research outputs/patents and make them available for the industry through what is called “universities spin-offs” or “knowledge spillover” (Scoreboard, 2015; Smith and Bagchi-Sen, 2012). For example, Delgado et al. (2014) proved that patenting has a positive impact on the overall regional economic development. However, in the latest studies, patent and research outcome is considered as a “*weak*” *indicator* on business cluster performance, e.g. (Breschi et al., 2001). Moreover, Baptista and Swann (1998) argued: “*patents can be a measure of inventive output but hardly of innovative success*”. The focus will be on the patent financial output and (licensing income). However, when companies start to license patents and products, this indicates a recognised product/company. This study will examine patents and license income, considering it as an *essential indicator.*

Research collaboration is another factor influencing the relationship between firms and universities, which is shaped by the type of targeted knowledge (“explorative” or “exploitive”). Explorative knowledge comes though research, which leads to more radical innovation (developing new idea), while exploitive knowledge is more related to improve knowledge stock of firms. Firms may seek either type of knowledge through university-firm networking (Huggins et al., 2011).

Provide the needed training and consultation services for the start-ups and mature firms within the cluster. Moore et al. (2004) determined that many start-ups struggle in managing businesses, and many of the entrepreneurial have difficulties in understanding business processes. Therefore, some universities have developed training programs which were very efficient in preparing the “new” business leaders. For example, Klofsten (2000) reported 80 new establishments all over Sweden, resulted from the development program prepared at Linköping University. The programme were delivered at 7 different places in Sweden [see (Smith and Bagchi-Sen, 2012) for Oxford University entrepreneurial program, for recent reviews on the role of universities in business clusters see (Lecluyse et al., 2019), and (Valero and Van Reenen, 2019) for general role of HEI on the overall economic development)].

Generally, universities are considered as one of the primary sources of knowledge benefiting firms, both on-cluster and off-cluster firms. It is contribution to knowledge stocks is widely acknowledged. However, the amount of university impact depends on many factors. For example, close proximity is a very important for regional firms benefiting from new universities, while old and prestigious universities may have broader relationship exceeding the geographical boundaries of the university (Huggins et al., 2012), which is emphasising the role of HEI as part of the triple helix theory and Science and Technology Parks.

2.4.3 Public / Governments

As clusters are considered a fundamental entity, which facilitates and stimulate regional growth, government and/or public authorities should – usually - encourage such initiatives. For example, in Singapore, public authorities have played a vital role in fostering innovation, providing fund, support higher standards of education as well as project management support (Watson and Freudmann, 2011).

First, they should provide the needed *infrastructure*. Recent research highlighted the importance of "*good infrastructure*" on SMEs export performance, e.g (Freeman et al., 2012). People do not want to move to dangerous places, and they want to be safe. They require good schools and health care systems (Watson and Freudmann, 2011). Based on this discussion. It is evident that having the needed infrastructure is a pre-condition for cluster development, and it is widely acknowledged as a success condition of regional economic development. Therefore, this suggests that *infrastructure* *availability* is "*important"* factor. Besides that, firms would inhabit a business cluster because it has an excellent infrastructure.

Tax reduction programs, availability of public R&D fund and other policies supporting young firms' growth. For example, Israel authorities provided a corporate tax reduction for the first seven years for companies establishing new businesses, where taxes reduced from 35% to 10%. Moreover, the government were providing up to 50% for specific R&D projects in which ideas were classified as important. However, it was argued that governments funded around 70% of the applied proposals (Wonglimpiyarat, 2016; De Fontenay, 2004). More factors include better immigration rules, facilitating foreign investments, encourage entrepreneurship culture [for the full set of policies which can stimulate clusters development see (Skokan et al., 2012)].

2.4.4 Venture capitals (VCs) and private investment

Private investments are very important "tool" used by entrepreneurial to commercialise their ideas (Wonglimpiyarat, 2016), sustain and keep the business running until it starts to pay off. Moreover, it helps in introducing innovations which improve firms' efficiency and profitability (Avnimelech and Teubal, 2005; Bertoni et al., 2011). For example, Grilli and Murtinu (2014) acknowledged that VC availability is one of the reasons for low economic growth for high-tech firms in Europe compared to the USA. Moreover, Davila et al. (2003) and Grilli and Murtinu (2014) reported a positive impact of VC investments on employment and sales growth and the overall performance of start-ups. Saxenian (2004) pointed out how the availability of foreign investment has played a crucial role in shaping the Taiwanese business clusters around minicomputers, ICs and computer hardware. It enhanced the knowledge spillover between already existing MNCs and local labour. These investments produced a knowledgeable set of labours able to build their businesses and use the experience gained while working for big corporations[4].

2.4.5 Cluster firms'

Developing healthy clusters depend upon well developed and healthy firms. So, the development of business clusters can be measured by its firms financial and innovation performance and capabilities.

Company organisation and re-organisation was reported as the main success factor for Fairchild in Silicon Valley. The same applies to ARM in Cambridge high-tech cluster, while lack of marketing strategies was the main obstacle for many firms such as Ionica (Athreye, 2004). It is also considered as one of the main contributions for adopting new innovations, where different organisation structures would have a different impact on firms' innovation capabilities (Padmore et al., 1998; Ethiraj and Levinthal, 2004; Lee et al., 2010; Shahzad et al., 2017). However, firms do not have the same learning capabilities, the quality and benefit of innovation are different too, where many innovation investments might fail (earlier studies estimated that 20% of innovation projects are profitable [see (Van der Panne et al., 2003; Stevens and Burley, 1997)], and others succeed . Furthermore, Cowan et al. (2007) argued that "*Cooperation between firms is also risky, and marked by uncertainty regarding a partner's skills, goals, and reliability, as well as the pair's ability to work together*".

4 The 153 reported VC companies along with around 350 return engineers from Silicon valley has also played a vital role in fostering Hsinchu Science Park in Taiwan (Bresnahan and Gambardella, 2004).

Khanna et al. (2016) summarised innovation success factors into four categories, which are firm, project, product and market-related factors. For firm related factors, they highlighted the importance of firm culture, managerial experience, team structure, strategy, and organisational structure in achieving higher innovation success rate. Indeed, the role of organisational structure in innovation adaptation and diffusion was furthermore emphasised by (DeCanio et al., 2000), who suggested two important roles of firms' organisation on its behaviour. First, it impacts firms' performance, through the speed of ideas diffusion, second through its impact on the organisations' individuals. However, there is no organisation structure, which is good under all conditions. For example, Chang and Harrington (2000) suggested that decentralisation is a better structure (in retail business) when the market is more stable, and consumers behaviour is not changing, however, when the market is not very different (between stores). On the other hand, innovation failure can be useful in some cases, especially with exploratory innovation, and if it stimulates firms' learning capabilities, which may results in a good innovation later on (Khanna et al., 2016). However, this is not the purpose of this study, but recent reviews can be found in (Shahzad et al., 2017; Navimipour et al., 2018).

Moreover, firms' performance has been used by many scholars once benchmarking business clusters. Temouri (2012) used firms' employment growth rate, turnover, profitability and financial viability for clusters evaluation and benchmarking [see (Ramírez-Alesón and Fernández-Olmos, 2017; Diez-Vial and Fernández-Olmos, 2017)]. While Ratinho and Henriques (2010) added job creation, the number of university graduates and the origin of the company for evaluating the impact of both science parks and business incubators. However, typically, it is very hard for start-ups of knowledge-based companies to start generating a profit in the first few years (Folta et al., 2006). Therefore, this study suggested that *turnover* can be used for evaluating the economic growth of companies.

Business clusters are supposed to stimulate firms' innovation which is defined as finding new ways of working, adapting or creating new processes to improve companies' efficiency (Bell, 2005; Mellor, 2011). Although it was argued that the financial and employment growth impact of innovation might be hard to notice. This can be due to, for example, innovation activities can take a long time to provide financial feedback (introducing new process/product will take a while until its effect starts to appear in term of efficiency or financial return) (Baptista and Swann, 1998; Lamperti et al., 2015). García-Manjón and Romero-Merino (2012) used *R&D expenditure* to explain firms' net sale growth. They proved a strong statistical correlation between R&D investments and company growth in high-technology and medium-high-technology industries when using quantile regression technique. In addition, Mudambi and Swift (2011) demonstrated a strong correlation between *R&D expenditure volatility* and firms' sales growth in what is called "fast clock speed industries" such as the ICT industry. However, this study discovered that correlation is decreased when companies get smaller, but business clusters mostly include SMEs.

Moreover, other identified indicators were networking and partnership agreements ("social glue", coordination and Inter firms' connectedness [see (Morosini, 2004; Pitelis, 2012; Casanueva et al., 2013; Zhang et al., 2017)]. Furthermore, Bell (2005) used the formal and informal relationship between managers and firms (networking) to model innovation. On the other hand, a 3D model was used to help to understand the performance of SMEs based on the DI number, annual turnover which helps to identify where is the organization at the current stage and how it can move into a better position, and the cost attached to the improvement (Mellor, 2011). Given the importance of networking, this study will explore the role of socialising in innovation production as well as connecting innovation development with employment and financial growth.

2.5 Knowledge sharing, innovation and cluster structure

Networking and partnerships have been identified as major determinants benefitting corporate innovation through knowledge sharing and transformation [see e.g. (Morosini, 2004; Pitelis 2012; Mellor, 2015)]. Empirical studies of business cluster success factors through the cluster life cycle have identified networking and trust as recurring success factors which are very important in all stages of cluster evolution (Tavassoli and Tsagdis, 2014). Ting Helena Chiu (2008) contributed towards understanding that the more central a firm is in the network, the more innovative it is. While Saxenian (1994) argued that positive rivalry sprit was one success indicator, where competitors have no problem in contacting each other, using the power of informal networking to solve regular issues and exchange new ideas, seek finance and solve day to day issues. Indeed, Mellor (2015) showed that such "just-in-time" knowledge is nearly as powerful as original home-grown innovations.

The "Porters diamond" allows researchers to distinguish between, e.g. firms and their suppliers, firms and customers, firms and higher education institute(s) and within firms themselves. Although Porters' diamond contributes into understanding how each component of it adds into the overall knowledge (knowledge stock) of the cluster, *it does not distinguish between different business clusters' topologies and how they best fit into different methods of building them* (top-down or bottom-up) (Porter, 1998). Moreover, Iammarino and McCann (2006) compared transaction costs and innovation within business clusters exhibiting three different topologies. Their findings included:

1. Personal relationship and social network: Transaction costs are minimised by "trust" between organisations, although building a trust relationship requires a long-term relationship.

2. Complementarities effect: The relationship between firms and their suppliers, and other forms of partnership.
3. The industrial typology of input-output: A long-term investment distinguished as having expensive entry and exit costs.

Networking involves knowledge and innovation sharing through formal and informal channels. At the firm level, a 3D model was proposed in (Mellor, 2011) to connect innovation with organisational performance to understand the effect of departmentalisation on firms' performance. Between firms, formal channels include inter-firm relationships as well as informal channels like personal relationships. Bell (2005) investigated the outcome of social and formal networking in a Canadian mutual fund cluster. He argued that the more informal and socially networked the managerial team is, the more positive impact they had on firms' innovation albeit that the information source may limit the information they provide, but that (in turn) did not have a significant impact on the overall innovation output. Social asset (networking) was reported to be more prominent in close proximity firms, which resulted in a higher innovation outcome for small firms, while formal alliances are more for firms' relationship with the outside world (Huggins and Johnston, 2009). On the other hand, it is also clear that large amounts of networking resources do not automatically imply good innovation (Guan and Chen, 2010; Huggins and Johnston, 2009), and that networks with little and no learning capabilities are ineffective (Gilbert et al., 2007).

Bathelt et al. (2004) distinguish between knowledge acquiring by relatively freely available knowledge inside a community "local buzz" exhibiting close proximity, or investments named "pipelines", which generally occur with the outside world (i.e. outside to the cluster). Pipelines transfer codified knowledge, while the local buzz is more tacit. However, these authors do not consider the acquisition of new knowledge or how this can benefit the cluster. Tacit knowledge sharing is one of the main factors that sustain business clusters (Bathelt et al., 2004; Breschi and Malerba, 2001; Maskell and Lorenzen, 2004). An informal and formal channel of networking enhance trust, which in turn decreases friction in the knowledge transfer process between firms, provided it is up to date and that firms can avoid any lock-in effects (Breschi and Malerba, 2001; Tallman et al., 2004). However, building trust requires time and investment primarily through informal channels (Iammarino and McCann, 2006). Some knowledge is proprietary, private within the firm and is prevented from leaking. While “architectural knowledge” can be shared, which addresses how firms organise, share, using and adapt any knowledge obtained, because it is rarely immediately applicable and needs adaptation to the new situation (Maskell, 2001). There is evidence implying a relationship between explicit knowledge and process innovation, while tacit knowledge was found to be more related to product innovation (Casanueva et al., 2013).

Eisingerich et al. (2010) emphasised the role of social networks on sustaining cluster performance. They defined “network strength” and “network openness”: Network strength is the regularity and depth of the interaction, trust, and “stability of the connections”, while network openness is measured by the ease of acceptance of new members into the network, links to the outside world, and the “diversity” of the members. In times of industry uncertainty, strong networks decrease the performance of a cluster, while network openness had a positive impact on cluster performance. Similarly, a “small world” network structure between cluster organisations discussed by (Kajikawa et al., 2010), where path length between organisations and a clustering coefficient were used to distinguish it from random-walk network structure. The small-world network can be distinguished by shortest paths between firms, and the availability of network shortcuts to reduce path length. Overall, the findings from eight Japanese clusters suggested that network impact is positively related to the network size combined with “small world” formation, meaning that the larger the network, the more benefits are expected to be gained by participating firms (Kajikawa et al., 2010). He and Fallah (2009) confirmed that networking has a positive relationship regarding innovation and cluster development in a mixed topology structure, where the degree of connectivity may be an indicator of the cluster development stage. Breschi et al. (2001) added that the lack of university-industry network caused clusters to decline or fail. This again underlines the importance of continuous innovation, disseminated by an innovation network, in building a sustainable business cluster.

Knowledge transformation through networking links would usually shape the networking structure within the cluster. Indeed, Markusen (1996) distinguished between four different types of business clusters: First, the "Marshallian industrial districts" when firms' connections are built around suppliers that are off-cluster, plus small on-cluster firms and customers relations (off-cluster firms). In this case, the on-cluster firms shape a randomly connected network with very high flexibility regarding labour movement within the constituent cluster firms. Because of the tendency towards specialisation in the same industry sector, there is a parallel tendency to improve the knowledge stock inside the cluster as tacit knowledge is transferred through employees' movements between firms, while codified knowledge moves through formal channels, e.g. suppliers' pipelines.

Second is the "hub-and-spoke" district, where the business cluster is built around one or more dominant large firms in similar industries. This type occurs when there are one or few central organisations and all other firms connect to the centre through ties that can consist of, e.g. spin-offs or informal social connections. It implies a strong connection between on-cluster and off-cluster firms, but with less cooperation with competitors. In this form of business cluster, knowledge transfer is through the "hub" or central organisation, which is considered the primary source of knowledge.

The third type is "satellite industrial district"; which is a critical mass but can be quite challenging to consider as a cluster because it does not conform well with most definitions of clusters. It consists of a critical mass of organisations in non-related industries where the business cluster is built around small organisations or branches of larger organisations which are relatively isolated from each other and only connected to their headquarters or off-cluster customers. In this case, the main knowledge spillover occurs vertically between branches of a firm and its headquarters, with less cooperation between co-located firms.

Finally, the "state-centred" industrial districts, when business clusters are built around one or more government-controlled research institutions or state-supported cluster-coordinating organisations that provide infrastructure, i.e. a more STP type structure, where the central organisation (the cluster initiative or CI) is established. This may typically govern an incubator programme, and with time the incubated firms start to graduate and cluster around this central organisation as described in the "triple helix" model connecting public, venture capitals (VCs), and higher education institutions (HEI) [see e.g. (Klofsten et al., 1999; Etzkowitz and Leydesdorff, 2000; Kim et al., 2014)]. The proviso is that the networking structure within clusters may change over time as the cluster matures and the overall cluster topology evolves (Menzel and Fornahl, 2009).

As to topology, "Marshallian industrial districts" would be expected to be an adhocracy, which moves to a more centralist aspect in the "hub-and-spoke" district model. A "satellite industrial district" would be expected to exhibit aspects of a non-controlled multi-level model, while "state-centred" would (at least initially) conform to a star topology. Clearly, what is needed in all cases is a net increase in innovation capabilities that is large enough to produce more benefits than the investments spent to build and stimulate this network.

Thus, the costs of networking can be considered to be a form of transaction cost, but *all previous studies have neglected to consider the cost of obtaining knowledge in business clusters*. In this study, we argue that any transacted knowledge will not be available for free because it requires communication time, which has a cost attached to it. Moreover, the knowledge obtained will most often require adaptation and must be correctly interpreted by the receiving firm, thus incurring more costs [see chapters 6 and 7].

Because Markusen (1996) presents the most comprehensive view of business clusters architectures, we have chosen to build directly on Markusen's work to measure the networking cost and find the most optimal business cluster structure in chapter 6.

2.6 Business clusters lifecycle

Although it has been argued that business clusters might not follow a specific path of life cycle as it can jump between different stages (Martin and Sunley, 2011; Press, 2006; Menzel and Fornahl, 2009), but there are a number of stages which business clusters life can go through from initiation until destruction or renewing. It is crucial to understand how the business cluster moves through different stages, especially for the policymaker, to act accordingly[5].

Business clusters lifecycle can be described as a three-dimensional process (Figure 2.6). It starts by either create itself when a number of companies are concentrated at specific district, and local authorities and/or firms notice this growth and establish what is called cluster initiative to enhance and support the growth (bottom-up approach) (Menzel and Fornahl, 2009; DTI, 2004; Martin and Sunley, 2011)[6]. Alternatively, clusters can be initiated as a result of public/governments/local authorities' interest in establishing a top-down business cluster in a specific region (top-down approach) (Menzel and Fornahl, 2009; Saublens et al., 2016). Then clusters might enter a growing intermediate phase, where the number of firms and spinoffs are increasing, new companies are entering (some are exiting too). Moreover, firms' financial situation is improving, investors notice the potential growth of firms in that specific cluster and start to invest, the cluster becomes more specialised, and

[5] In order to make it understandable, we assume that business clusters might follow a specific lifecycle.
[6] Richmond council in London, UK has noticed a growth in the number of companies as well as employment in high-tech field there, then they call for a meeting at Sept, 2016 where interested companies meet and they are planning to build what is called Richmond new tech city.

employment growth can be noticed (Menzel and Fornahl, 2009; Bresnahan and Gambardella, 2004; Delgado et al., 2014).

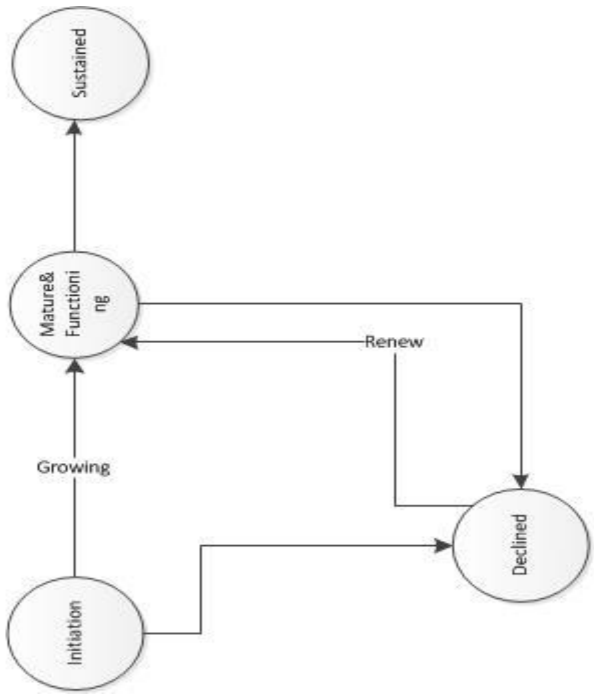

Figure 2.6 Business Cluster Lifecycle

After that, the growing cluster will go into a sustaining phase. In this phase, the cluster will – almost - keep the same level of employment growth, cluster specialisation and firms' entry rate. The cluster will – regularly – keep growing at this phase, but not as fast and frequent as the mature/functioning phase (Menzel and Fornahl, 2009). It might get into a technology lock-in, lack the adaptation capabilities and suffering from large firms exiting the cluster. This will cause an overall cluster performance to decline (Østergaard and Park, 2015; Sonderegger and Täube, 2010). However, this can be identified by looking into the behaviour of the success indicators. Then, it might be able to renew itself by improving its adaptive capabilities, create a new market opportunity which will make it enter into the growing phase again[7] (Sonderegger and Täube, 2010). Understanding the different stages that business cluster moves through is vital for different agents (component) of the business cluster, which might need to adapt to the current development stage of both micro-level (firm) and macro-level (cluster) (Pique et al., 2018; Li et al., 2018), similarly is the importance of different clusters' success factors [see (Tavassoli and Tsagdis, 2014)].

2.7 Benchmarking Cluster Performance

After understanding how each actor of business clusters contributes to business cluster development, it is crucial to understand what scholars and government used for evaluating cluster and its inhabitant's performance. Therefore, this section will discuss the different approaches used when evaluating business cluster performance. Ranging from statistical approaches to modelling approaches.

[7] It was reported that Silicon Valley has entered into a declining phase in early 1980s when Japanese start-ups started to attract more customers, but it was able to renew itself by introducing new products and innovation (Saxenian, 1994).

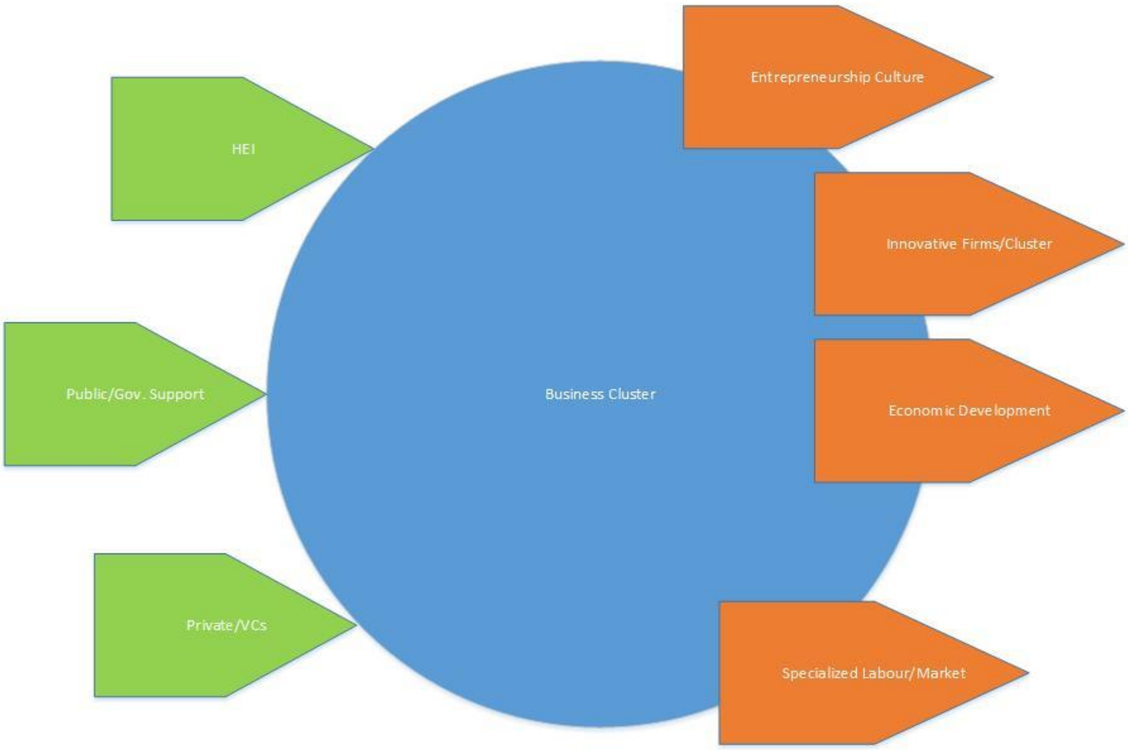

Figure 2.7 Business clusters input/output

Figure 2.7 summarises the main focus of previous benchmarking studies, which uses cluster actors as input and expect to get specific output. This section will focus on empirical input/output studies. Thus, the next section will discuss how statistical approaches were used for evaluating the business cluster.

2.7.1 Statistical approaches

Temouri (2012) studied seven indicators for 80 clusters in different industries and benchmark them during both pre-recession and recession periods. The study calculated the average number of indicators, e.g. average employment growth in firms over two years during the two periods and then finds the average of the seven indicators. This method can be used to benchmark different clusters and try to rank them for two years, but this measurement does not provide indications in which stage the cluster is. Moreover, it does not judge the current cluster performance. However, a performance measurement method should indicate weak indicators (indicators that need improvement, e.g. the innovation indicator (X) is performing poorly and needs to be improved), and what needs to be improved to stimulate clusters' performance, which was not handled in the proposed method.

Moreover, regional innovation scoreboard (RIS) 2006 applied a star model for evaluating clusters all over Europe. Stars were assigned based on measuring employment within the cluster, specialisation quotient and cluster employment position within the region (Scoreboard, 2015). This method gives hints on which indicators can be used when measuring clusters' performance but does not provide a methodology for doing that. However, a more sophisticated statistical performance used for "benchmarking" innovation for union members based on 25 "suggested" indicators grouped into different categories (however, they used 12 indicators, since the other 13 was not available). This method was only used for benchmarking regional development at the state level, and it does not provide a mechanism for evaluating "high-tech hubs" at the regional level (Derbyshire et al., 2012).

Porter (2003) pointed out that there is no strong correlation between starting salaries and employment growth. However, there is a weak but significant relationship between employment growth and wages growth. However, he found a very strong relationship between patenting, employment growth and average wages. Although this method can be used for studying different parameters effects on financial development, it neglected that start-ups can be established by employed people. Therefore, it might not indicate that a firm is performing financially well.

On the other hand, Delgado et al. (2010) tried to explain the emergence of clusters by measuring the entrepreneurship activities using two indicators, which are 1) the number of newly-established firms and 2) the employment growth in the new establishments in cluster region and surrounding regions which they called as complementarities. Moreover, it used the specialisation quotient as a method for measuring the cluster strength. This study emphasised the fact that stable clusters will foster more entrepreneurship activities, although it can have a convergence effect at initial stages of cluster formation. However, this does not explain why a cluster can go into declining or growth mode. Although it introduced a mechanism for evaluating the cluster strength, which can be used for identifying *potential* clusters, however, that would work for already established clusters [see (Delgado et al., 2014)].

Menzel and Fornahl (2009) introduced a mechanism for identifying different stages of business clusters based on the indicators: number of companies and employees, and clusters' heterogeneity and networking factor. Their conceptual model encapsulates the hypothesis of how the business cluster can move between different stages. For example, business clusters can jump between different stages and move from growing into declining or keep sustaining without declining. Clearly, one wishes to avoid the path, which leads to clusters' destruction. However, their contribution was purely theoretical, and there is no empirical evidence. Moreover, this method lacks a formal model on how to improve the performance of the cluster in different stages.

However, recent studies used on- and off-cluster firms' development to measure its performance based on similar matrices. These studies include (Al-Kfairy et al., 2018) (see Chapter 4: and 5), and (Diez-Vial and Fernández-Olmos, 2017; Vásquez-Urriago et al., 2016). Among other indicators, they used R&D, social expenses, turnover, patents data, firms' sizes, firms ages. They provide a systematic way of measuring clusters' performance and thus use these indicators for extracting clusters' success factors. This approach further analysed and extended in Chapter 4: and Chapter 5.

2.7.2 Qualitative approaches

A framework was introduced to measure seaport clusters performance, which was based on two main indicators: cluster structure and cluster governance. It evaluates different variables such as – for cluster structure – internal rivalry, cluster obstacles, cluster diversity and more. For cluster behaviour, it assesses different variable, e.g. trusts, presence of leading firms. It collects data through industrial interviews and surveys (de Langen, 2004). On the other hand, Bigliardi et al. (2006) used clusters' mission and strategic reports to build an evaluation framework.

Moreover, Guadix et al. (2016) used a questioner-based analysis to evaluate the importance of different success indicators found in the literature. They assessed clusters revenue and population (workers). Their findings underline the importance of investment, internationalisation, networking, and incubation in sustaining and enhancing business cluster performance. Although they contributed to identifying the needed policies in order to improve underperformed/young cluster in the Andalusia area (Spain), their findings are hardly applicable as they are based on comparing different clusters' performance. Moreover, they grouped the cluster in the Andalusia area only and assessed the performance relatively. On the other hand, cluster performance is a collective of its inhabited firms' performance, which has not been evaluated in this study.

Generally, most of the qualitative approaches used are based on literature reviews, examples studies include (Martin and Sunley, 2003; Eickelpasch et al., 2007; Padmore and Gibson, 1998) and most recently (Al-Maadeed and Weerakkody, 2016; Pique et al., 2018). However, qualitative approaches alone do not provide a comprehensive way of measuring the clusters' performance. It should be either a combined mechanism of qualitative and quantitative approaches or otherwise use a quantitative approach to build a qualitative hypothesis. This thesis combined the conceptual models with empirical studies to build a more comprehensive view of cluster innovation success factors.

2.7.3 Modelling approaches

An early Modelling approach was proposed in (Padmore et al., 1998) to analyse the weakness and strength of a business cluster. The model analysed Grounding, Enterprise and Market (GEM), and used six indicators (which are infrastructure, local and external market, companies' organisations and competition and suppliers, and resource availability). Then, it scores (from 1-10 for each factor) factors for analysing clusters performance. The model used different statistical methods for evaluating business clusters, but it just looked at innovation capabilities. However, it provides an infrastructure for modelling business clusters. This modelling approach can be extended to measure financial and entrepreneurship behaviour of science parks (Padmore et al., 1998)[see also (Padmore and Gibson, 1998)].

Lin et al. (2006) applied a system dynamic modelling technique to study the effect of "feedback" on business clusters, which used for evaluating knowledge spillover between CIs and clusters' firms. However, this was only used to study the effect of knowledge spillover, and it does not evaluate the overall cluster performance. Furthermore, an analysis of patent networking in New Jersey and Texas telecom districts was suggested to understand the emergence of business clusters. It suggested analysing inventors and organisation networking. Although their approaches provide a way for understanding knowledge spillover, and how networking helps improving innovation, it does not give any connection with other dimensions of cluster performance indicators (He and Fallah, 2009). However, networking and knowledge spillover impact on business cluster innovation outcome is further analysed in chapter 6. In order to understand the evolution of business clusters, Lombardi et al. (2012) used the Analytical Network Process (ANP) based on its triple helix components. However, the model was "pure" conceptual and based on a theoretical understanding of the main components and indicators.

Diez-Vial and Fernández-Olmos (2017) applied panel data modelling (dynamic model over time) with random effect to measure the impact of firms age, size, innovation, and industry maturity on the firms' growth inside science park (cluster) using 12,800 firms. They evaluated sales, and employment growth (using the natural logarithmic difference between time (*t*) and (*t-1*), while the measured innovation using the ration of new products (to the firm, and market) sales to the total turnover. Their finding suggested a negative impact of firms age on both sales and employment growth, while firms size has a positive effect on growth parameters. On the other hand, industrial maturity had a nonlinear impact on both growth parameters, while innovation reported having a different impact based on which parameters were used. Although these model helps to understand the impact of industrial maturity, age, and size of firms' growth and innovation. However, they built their conclusion (regarding firms age and size impact) based on only the linear impact, where they stated that the cluster impact is positive in early firms age, but less on the later stages, which is more like a quadratic effect [see Chapter 5].

On the other hand, Østergaard and Park (2015) identified some declining factors. Some of the factors identified are: "technology lock-in", the exit of both multi-national corporations, and new firms and lack of adapting capabilities such as adapting new technologies capabilities. Moreover, Breschi et al. (2001) summarised that having few numbers of start-ups, less specialised labour, weak government support and lack of university-industry network caused clusters to decline or fail.

It is obvious that there is a gap in understanding clusters success factors and indicators. Moreover, we lack a systematic and defined approach to identifying and evaluating business clusters' success indicators and factors. While there are many studies evaluating business clusters success, but most of these studies focus on only one component of the system, e.g. financial performance or innovation capabilities. In this study, we used business clusters' success indicators for extracting success factors, as well as analysing the impact of different business clusters structure on clusters' performance. Next section will summarise the findings in this chapter.

2.8 Summary

It is essential to understand that business clusters have been transformed from being a critical mass of organisations(firms) into a more organised entity (set of connected firms), which is occurring as a result of local and regional authorities' concentration on these development eco-systems. This resulted in transforming the classical view into the triple helix and sometimes a quadrable helix view (Leydesdorff and Etzkowitz, 2003), which supported by large organisations such as EU commission (Nauwelaers et al., 2014; Saublens et al., 2016). Cluster organisation is critical as it shaped how knowledge is moving between different cluster actors. Therefore, this chapter summarised each actor (component) of the whole eco-system using triple helix view of regional development.

The well-known cluster life-cycle model is the one presented at (DTI, 2004) and (Menzel and Fornahl, 2009), which present the different stages that business clusters go through. The importance of these models lies in understanding how each component of the business cluster should react in different development stages, which was recently discussed in (Pique et al., 2018). Moreover, in this thesis, we modelled how firms and business cluster (from an organisation perspective) must react at different stages of firms and clusters development life cycle (see 5.3.4 and Chapter 6:). However, a cluster topological and organisation structure will be further discussed in Chapter 6.

Then, the different approaches used for evaluating business clusters were studied. Table 2.1 summarises the indicators used in the literature for evaluating different components of the business cluster. Performance indicators used can be divided into employment, firms’ financial situation, entrepreneurship, and innovation.

Table 2.1 Success Indicators as in Literatures

Employment measures	
Employment	Used for calculating LQ, for identifying employment growth. It is a crucial indicator.
Employment growth per cluster/per firm	
Entrepreneurship	
Throughput	Measure the firms entering growth. It uses the formula (for cluster i, and year j). Throughput(i,j)= (Number of firms(j) – number of firms(j-1))/Number of firms(j).
The overall number of firms	It is based on the number of firms in each year (j).
Number of new establishments	It is based on the formula (for cluster i, year j and the number of MNC n). New establishments(i,j) = Number of firms(j)- number of firms(j-1) – MNC(j)
New firms under the mission of creating new product or services	-
Innovation	
Number/average of patents	Total number of patents within-cluster or the average number of patents per employee
Patent and product licensing outcome	Total income of patents and product licensing as a measurement of innovation output
Networking with the cluster	Number of network connections between CIs and Cluster firms
Partnership agreements within and outside the cluster	The total number of partnership agreements between firms' cluster and outside cluster firms.
Social networking	Indirect connections between cluster firms
R&D expenditure	Total R&D expenditure within-cluster firms
R&D expenditure volatility	

Financial behaviour	
Profitability/average profitability	Total net profitability within clusters firms or average per employee
Turnover/average turnover	Total cluster firms turnover or average turnover per employee
Total/average asset value	The total asset value of cluster firms or the average asset value per employee in the cluster.
Average salary and salary growth	Average salary per employee within-cluster firms and salary growth within-cluster firms.
Total investment within clusters' firms	

Moreover, most of business clusters' studies focused on clusters' benefits, comparing different business clusters, or theoretically try to evaluate different business clusters. Methodologies used for evaluating business clusters either focused on one component of the whole system such as Location Quotient (LQ) (the ratio of sector employment (at the regional level) to regional employment divided by the ratio of sector employment at the country level to the total employment at the country level) and innovation network or use simple statistical approaches for benchmarking business clusters. However, there were some tries to use computer modelling techniques with business cluster, but, they were either conceptual or lack empirical evidence, single study component of business cluster or with different goals other than performance measurement. However, it worth highlighting the purpose and usefulness of different modelling approaches used to meet different scholars' goals [see Table 2.2].

This underlines the importance of building a framework, which can be used in evaluating business clusters and give indications on how their performance can be improved. It shows the importance of finding a way of evaluating if a set of firms located outside the cluster can establish a business cluster.

Table 2.2 Summary of Modelling Approaches

Modelling approaches	
Model	Comments
Patent networking	As the patent indicator is considered a weak indicator, so the patent networking.
ANP	Can be extended to handle innovation networking
N/K model	Cab be used to test the clusters evolution hypothesis
Complex adaptive system	Can be used to test cluster life cycle hypothesizes

Chapter 3: Context, Data Source and Methods

3.1 Introduction

This chapter sets the foundation for the overall research methodology used in this research. It starts by reviewing the methodology used for the overall project (section 2), then construct the conceptual model used for extracting the business cluster success factor. It evaluates three different dimensions of business clusters' success indicators (innovation, financial situation, and size) in section 3. Section 4 introduces the case study (MSP), analyse, and review the literature relevant to it. Moreover, it constructs the structure of MSP and the development over its lifetime.

Furthermore, section 5 defines the data sources, data cleaning and MSP borders between on- and off-cluster firms as well as the different levels of analysis. Section 6 summarises the chapter.

3.2 Research Methodology

First, it is started by conducting a very intensive literature review to be able to understand the "modern" business cluster ecosystem, success factors and success indicators. Moreover, it hunted for performance measurement methods used in different studies, which led to identifying the factors influencing them.

Different databases and libraries have been used, e.g. "google scholar", "researchgate" and Kingston University library catalogue to explore relevant literature. Among others, the following search phrases were used:

1. Business clusters/tech-hubs/science parks success factors/indicators.

2. Failure in business clusters/high-tech clusters/tech-hubs.
3. Tech-hubs/science parks/business clusters modelling.
4. Business clusters life-cycle.
5. Knowledge-based economy.
6. Modelling/performance of triple-helix.
7. Measuring/evaluating business clusters/tech-hubs/science parks success.
8. Porter Diamond.
9. Porter business clusters.

The results of the research were first evaluated by scanning the abstracts to evaluate the relevance of each literature. Some literature led into other referenced researches as critical to review. In general, we tried to review modern and theoretical literature which were identified to be relevant to these research questions.

Reviewed literature helps to build a comprehensive view of the methods used for evaluating business clusters. Moreover, it helped in distinguishing between business cluster success indicators and success factors. However, in order to find out if our understanding of the difference between factors and indicators is correct, we get back into Oxford online dictionary[8], which reported that a factor is "*A circumstance, fact, or influence that contributes to a result*", while an indicator is "*A thing that indicates the state or level of something*". Generally, this means that a factor is used to predict an indicator. This distinguish helps in building the conceptual model (section 3).

Then, a case study has been identified. The case study has been selected to be Linköping city science park named as Mjärdevi Science Park (MSP), which is located around 200 KM south of Stockholm. Linköping has a long reputation as both industrial

[8] https://en.oxforddictionaries.com/

and technology city with a well-known university named Linköping University. Linköping was for the long-time home of large branches of Swedish corporations and Swedish government research centres such as Ericsson AB, SaaB aircraft division, Institute of Forensic Genetics and Swedish Geotechnical Institute (Klofsten et al., 1999; Hommen et al., 2006) (section 4).

After that, the dataset was collected from "Ratsit" [9] Swedish database of companies and persons for all firms located in Linkoping with industrial code "62", which represents programming and related industries[10]. The data were categorised and analysed as discussed in section 5.

Then, the collected data put into Minitab, SPSS, Matlab, Stata and Maple to statically analyse them to obtain a meaningful combination of data and extract the most critical factors. It started by distinguishing between on- and off-cluster firms then identify which group is performing better. Then, it resulted in several multi-dimensional models which can be used to identify the status of the business cluster and how to improve its performance. Moreover, it helped in identifying business clusters success factors as well as the needed policies for sustaining business clusters development.

Table 3.1 List of Used Tools and the Purpose of Each Tool (alphabetical order)

Tool	Version	Usage
Maple Software	17	Used for plotting different equations generated from the regression analysis.
Matlab	2016R	Used for programming of different Monte-Carlo simulations.
Microsoft Excel	2017	Used as an intermediate medium for storing and analysing the data. The raw data came first in excel format, which was initially cleaned up there.
Microsoft SQL Server	2017	Used to store the dataset, and run the quick query for categorizing data (based on firm age, size, ..etc)
Minitab	17	Used for analysing data (initial analysis), especially at the aggregate level. its scatter plot function was used for plotting some of the simulation outputs.
SPSS	24	Used for analysing some of the data for the on- and off-cluster groups.
Stata	14	Used for building the fixed and random effect panel data models.

[9] https://www.ratsit.se/
[10] http://www.sni2007.scb.se/snihierarkieng.asp?sniniva=2&snikod=62

After that, we used Monte Carlo analysis (Davis et al., 2007; Chib and Greenberg, 1996; Robinson, 2014) to evaluate different scenarios to understand the impact of each success factor in different scenarios and to identify the best structure (networking topology) for business clusters. An approach which is widely used for extracting theories by experimenting different scenarios [see (Al-kfairy et al., 2019a; Al-kfairy et al., 2019b; Will et al., 2019)] Moreover, each of the following chapters will discuss intensely the methodology used in it, as we applied a number of approaches in our experiments. In conclusion, following these steps points out some important policy implications, which can be derived from the resulted models. Table 3.1 shows the different tools used thought the research journey, while table 3.2 maps the different methods applied.

Table 3.2 Overview of Used Methods

Used Method	Objective	Chapter, Section
Data comparison/ basic statistical analysis	Compare on-cluster and on-cluster firms performance using total turnover, patents, number of employees and number of firms.	Chapter 4
Regression analysis	To extract business cluster success factors from the set of success indicators at the aggregate level.	Chapter 5, section 5.3
Panel data analysis	To find the set of on-cluster as well as off-cluster set of success factors.	Chapter 5, section 5.4
Monte-Carlo simulation (agent-based simulation)	To simulate the different business cluster organisation structures using networking cost, innovation type and quality of cluster managers.	Chapter 6 and Chapter 7

3.3 Modelling Approach and Conceptual Model

Following (Robinson, 2014) on modelling activities. Modelling lifecycle should contain the following activities:

1. Understanding the problem that will be developed. In this step, one should collect as much information as needed to understand the problem. We used literature review for that purpose. This helps in understanding the gaps in the literature and therefore define the needs. This step was done as part of chapter 2 of literature reviews.
2. Based on the theoretical understanding of the problem, a conceptual model follows. A conceptual model defined as "a description of the model that to be developed" (Robinson, 2014 pp.65).
3. Model implementation "computer model" which is the actual simulation or statistical model of the real-world problem. In this research, the model is a set of statistical models based on linear, non-linear, and panel data regression together with Monte-Carlo based simulations.
4. Model verification and testing to check the accuracy of the developed model, this is done using statistical checks, e.g. p-values and R^2 values.
5. Then, model improvements based on the tests or end-users' feedback, this is left as a future work, where more case studies can be checked.
6. Finally, implementing model findings/results to solve the real-world problem, which is done by extracting a set of policy implications and recommendations as presented in the conclusion chapter.

These steps were followed carefully from literature review discussed in section 2 of this chapter to policy implications and recommendations done in the conclusion chapter. Next section will discuss the conceptual model.

3.3.1 Conceptual model

After reviewing enough literature regarding business cluster success indicators, it is observed that the majority of them looked at three different indicators for the success in a business cluster which are the growth in cluster size as well as the growth in its inhabited firms, innovation capabilities at both aggregate and micro-level, and the financial situation. Scholars used different approaches in measuring these indicators and the factors influencing them.

Therefore, it is assumed that the business cluster success indicators will follow the evaluation triangle presented in figure 3.1. It implies that we will use the measurement of cluster financial situation, innovation capabilities and size (entrepreneurship activities) activities. However, these variables are purely conceptual, meaning that the formulas to calculate each input variable is not defined in this section. Formulas will be based on the data analysis of the case study. Then, we will use the variables affecting these indicators to extract the success factors.

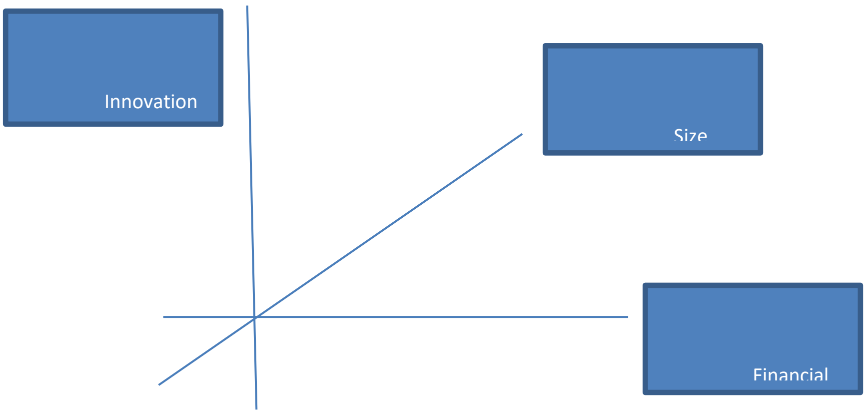

Figure 3.1 Business Cluster Evaluation Conceptual Model

This model presents the foundation for measuring the success of the business cluster, and factor influencing its development. However, these measurement dimensions are still vague. Therefore, the aim is to complement the earlier understanding of the model by classifying the data categories from the data set into each dimension in the model (figure 3.2).

Figure 3.2 Conceptual Model Revisited (more Details)

In chapter 2, we discussed different proposed methods for measuring different indicators of successful firms and business cluster. Then, those indicators were summarised in Table 2.1. However, the obtained data limits the study to focus on the available data, which can then be narrowed based on earlier discussions. Moreover, this study is an exploratory study, which means that we will try different models to find the best fitting model based on different criteria, such as p-value and R^2.

Figure 3.2 shows the data of our interest (after intersecting the available data categories from the data set, with table 2.1 and 2.2 categories) based on the conceptual model. However, these data are used at both aggregate and micro-level analysis. Next section goes through the case study used for obtaining business cluster success factor and analyse it.

3.4 Case study

As an example of the "top-down" approach of business cluster development, Linköping Science and Technology Park (STP), named as Mjardevi Science Park (MSP) in Sweden was selected. Linköping city located around 200 KM south of Stockholm (the capital of Sweden). It is considered as one of the most successful technology-based cities in Sweden with a very high-profile research university (Linköping University) (Klofsten et al., 1999).

Historically, the city moved through different development stages employing several industries. Starting in early days of 20th century, the city was dominated by metal industry, moving on into establish Saab aircraft division in early 1940s, then Linköping university was established in 1969 along with a planned Science park which encouraged technology-based, and knowledge-intensive firms to open branches closed to the university, e.g. Ericsson and more university spin-offs were established (Klofsten et al., 1999).

The Foundation for the Development of Small Businesses in Linköping (SMIL) and Mjärdevi Science Park (MSP) founded in 1984 with six firms employing 150 (Mjardevi Science Park, 2016). Since then, the city experienced rapid growth in the knowledge-intensive sectors (image processing, digital TV, wireless communication and software development services) with over 300 firms employing more than 6,000 (Mjardevi Science Park, 2016).

The development of Linköping municipality area was studied from different perspectives. Klofsten et al. (1999) analysed it from triple helix theory with the historical development of the city as an example of triple helix phenomena. Hommen et al. (2006) focused on the factors enhancing success in earlier stages of the science park developments. They used MSP as a successful example. They highlighted the importance of Linköping University in establishing and sustaining the science park development, through university spin-offs (counted for 100% (in early-stage (Mjardevi Science Park, 2016)) and filling in the needed expertise (other sorts of support are available in (Klofsten, 2000). Other factors indicated were longitude history of "industrial infrastructure" and availability of MNC large firms, e.g. Ericsson and SAAB, enhancing entrepreneurship culture and support through central organisations (SMIL and MSP) and incubators' programs. On the other hand, (Tavassoli and Tsagdis, 2014) built on literature review of CTI cluster studies on success factors e.g (DTI, 2004), triple helix, and (Menzel and Fornahl, 2009) model of business clusters' life cycle to identify the importance and relevance of each success factor at each cluster development stage (birth, growth, sustainable and declining). They underlined the importance of the networking and entrepreneurship culture through all development stages compromising a stable importance level (4/5) (5 is the most critical indicators), while innovation and R&D seem to be more important at growth phase 5/5, and stable at all other stages 4/5.

Analysing previous studies of MSP, the started structure shows that, MSP organisation cluster initiative and SMIL, together with Linkoping University, form the central supporting organisations for the science park called Cluster Initiative (CI). CI is connected to the first six (C) established organisations, which together formed the heart of MSP.

Later on, the cluster started to attract MNCs, which acted as primary sources of firms' spin-offs, and knowledge spill-over. After that, MSP started to become more of a randomly connected business cluster model. This is presented in figure 3.3, which shows that CI is not acting as a central organisation, but more as a networking facilitator and run its internal incubation programme. It is essential to understand the cluster topology, to evaluate if it can be improved, or it compromises the best available topology.The case study was selected based on a number of criteria, which can be summarised in the following points:

1. It represents a knowledge-intensive industry.
2. The availability of data through different sources (research, website, Ratsit DB).
3. The availability of full historical details.
4. The cluster age, which makes it easier to follow the full development life cycle.
5. It represents a wide range of science parks as described in the latest IASP statistics, where most science parks have between 100 – 400 employees (around 50%), and 85% of them contains computer science industries, which is the main reason of selecting SIC code 62X as our sample.

Next section presents in more details the different data sources used for collecting MSP data.

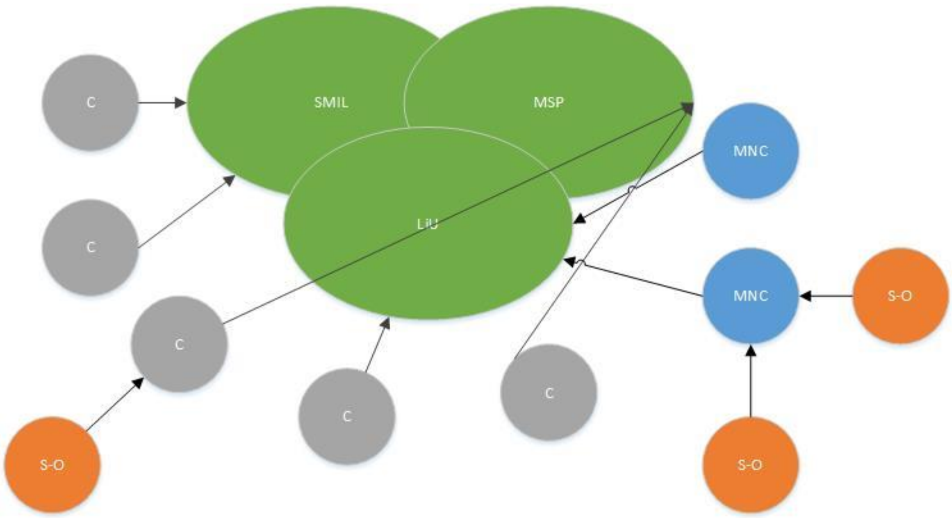

Figure 3.3 Simplified View of MSP Current Structure

3.5 Data sources and analysis

This section describes the data sources and the collected data. Next, the clusters' borders will be drawn, then, the analysis approaches and levels will be discussed.

3.5.1 Data sources

This project obtained data from different sources, as follows:

1- The science park website, which included a short history of its development, however, the website was updated during the project, and that page was not available to reference any more, but it was possible to find an older snapshot of the webpage from August 2016[11]. In order to overcome this issue, we studied different researches about MSP history and development, e.g. (Hommen et al., 2006; Tavassoli and Tsagdis, 2014) (
2-
3-
4- Table 3.3).
5- Swedish firm (ratsit) for collecting personal and companies' financial data was contacted to get more info about Linköping firms. We managed to get employment and financial data, which covers the period of 2007-2015. The data set contains firms' info with standard industrial classification (SNI) 62, which includes the following branches[12]:

i. Computer programming firms.

[11] We used the website https://archive.org/web/ to search for older versions of the website, then the older version of the website is available under https://web.archive.org/web/20160807084436/http://mjardevi.se/sv/om-mjardevi/historik

[12] SNI numbers and information were obtained from Statistics Sweden. The list of firms' branches with industrial code 62' can be found at http://www.sni2007.scb.se/snihierarkieng.asp?sniniva=3&snikod=620

ii. Computer consultancy firms.
iii. Computer facilities management firms.
iv. Other IT and computer-related firms.

Table 3.3 MSP development in numbers

Age	Total MSP Number of Firms	Total MSP Number of Employees	Source
1	6	150	(Hommen et al., 2006; Mjardevi Science Park, 2016)
5	18	300	(Mjardevi Science Park, 2016)
9	49	1,000	(Hommen et al., 2006; Mjardevi Science Park, 2016)
13	110	3,000	(Hommen et al., 2006; Mjardevi Science Park, 2016)
15	115	4,300	(Hommen et al., 2006)
17	150	5,500	(Hommen et al., 2006)
19	170	4,500	(Mjardevi Science Park, 2016)
21	NA	4,000	(Hommen et al., 2006)
22	210	NA	(Hommen et al., 2006)
23	228	4,700	(Hommen et al., 2006; Tavassoli and Tsagdis, 2014)
24	230	5,800	(Hommen et al., 2006)
25	NA	6,000	(Hommen et al., 2006)
26	NA	5,950	(Hommen et al., 2006)
32	NA	6,000	(Mjardevi Science Park, 2016)

NA Data is not available

3.5.2 Data cleaning, selection and cluster definition

This research follows a rigorous data cleaning and analysis technique. We have received data for 439 firms located in Linkoping with SIC code 62X for the period of 2007 – 2015, where the number of firms is different in each year due to new firms formation and bankrupted each year. The received data was in MS excel format. Data was first moved to SQL server to make data querying and cleaning easier. Next, a dummy binary variable called “On-Cluster” was created, the value “1” means that a firm is located on-cluster, and “0” if it is located off-cluster. In the first round of data cleaning the on-cluster and off-cluster firms were distinguished using the following criteria:

1. If the firm is in the main streets of Mjärdevi science park (Linköping), which are Datalinjen, Teknikringen, Diskettgatan, Wallenbergsgata and Universitetsvägen,
2. If a firm is in one of the MSP postcodes.
3. Otherwise, the company is initially added to the off-cluster group until we run the second round of data cleaning.

In the second round of data cleaning used Porter definition of the business cluster (Porter, 2003) and most agreed characteristics’ of Science Parks found in (UNESCO, 2017; European Commission, 2018; IASP, 2016), the process was performed manually and using MS Excel by applying the following criteria:

1. If a firm is part of Mjärdevi science park community and mentioned in its website,[13]
2. Alternatively, is part of SMIL organisation, which is the sister organisation of Mjärdevi science park community[14].
3. Otherwise, the company is added to the off-cluster group.

These criteria reflect the most agreed definitions of business clusters of being connected to a central organisation. This would also help in identifying the role played by CI in sustaining business cluster development. After that, data were divided into data for on-

[13] https://mjardevi.se/company/
[14] http://smil.se/medlemsforetagen/

cluster firms are 75 firms representing 30% of the total number of firms inside the business cluster, and the rest (364 firms) for off-cluster firms. Then, we loaded the on-cluster and off-cluster data files (in ms Excel format) to SPSS, Minitab and Stata statistical packages for further analysis (see table 3.1). Next section discusses the different level of data analysis performed throughout the research journey.

3.5.3 Levels of analysis

In this research, we analyse the dataset at three different levels:

1. Total values level (aggregate level): where the business cluster is used as one entity (equation 3.1), where c represents specific category such as "turnover", in year j, i is the firm index, where the business cluster contains N firms, thus the value c_i represent the category (c) of the firm index (i) (Table 3.4), and applying Equation 3.1 (see Chapter 4:)

$$C_j = \sum_{i=1}^{N} c_{i,j}$$

Equation 3.1: Total Values at the Aggregate Level of Category *C*

2. Mean level: in this case, we calculate the average value of the category based on the number of firms in the cluster. The mean values are calculated using Equation 3.2 (see Chapter 4:)

$$Vmean(C_j) = \frac{C_j}{N}$$

Equation 3.2: Mean Value of Category at Aggregate Level (to number of firms)

3. At the Micro level: where the analysis is done per-firm instead of the aggregate-level. Then, Panel data analysis was used (see 5.3.4)

Moreover, each chapter consists of a methodology section, which describes the data analysis technique and the method used when it is relevant.

Table 3.4 Total Values of Each Category

Cluster Age	Cluster NOF	Total Firms Turnover	Total Firms R & D	Total Firms P&L	Total Firms NOE	Total Firms SE
23	55	1,273,607	487,867	1,801	1,203	269,757
24	62	2,339,886	491,717	3,005	1,281	281,753
25	69	2,466,166	559,346	3,336	1,353	286,929
26	69	2,403,299	608,261	5,191	1,340	329,112
27	71	2,466,223	644,630	38,222	1,468	332,656
28	74	2,698,457	727,021	62,160	1,610	359,420
29	74	2,662,337	773,372	46,780	1,630	458,286
30	83	3,213,926	814,879	27,804	1,470	371,512
31	83	3,249,411	884,404	67,697	1,463	497,654

All values are in KSEK, except the age and number of firms

3.6 Summary

This chapter sets the foundations for the empirical part of this study. It defined the cluster borders and therefore distinguish between firms located on and off-cluster, which is crucial for evaluating the cluster efficiency (Chapter 4:) as well as modelling firms success factors (chapter 5 and 6). Moreover, it sets the level of analysis, where we analyse business clusters at the aggregate level and micro-level (firm-level).

In conclusion, this research starts by doing a comprehensive literature review, then collecting data from different sources. After that, we evaluate the efficiency of business clusters at the aggregate-level, which we then did at the micro-level. Then, Monte Carlo simulation was used to evaluate different cluster topological structure, which at the end helps to identify the needed policies for sustaining business clusters development. However, this study is data-driven study, which focuses mainly on extracting business clusters' success factor by exploring different statistical models, then use Monte-Carlo simulation to extend the state-of-the-art knowledge with regards to business cluster knowledge and innovation diffusion. Next chapter evaluates business cluster impact on its inhabitant firm's development using off-cluster as a control group.

Chapter 4: The efficiency of Business Cluster

4.1 Introduction

This chapter focuses on measuring the efficiency of the business cluster as a tool for fostering regional development. In order to achieve this goal, we use the conceptual model identified in 3.3.1 and the three-level of analysis (3.5.3). To get a more robust result, we use off-cluster firms' as a control group.

Thus, this chapter will investigate Linköping municipality in Sweden (the case study) which hosts a mature science park (Mjärdevi Science Park). The Swedish "Ratsit" database of firms in industry code 62X (computing-related) was used and the over 300 companies were divided into two groups; those inhabiting Mjardevi Science Park ("on-cluster" firms) or those in Linköping municipality, but not in Mjardevi ("off-cluster" firms).

All firms were firstly divided according to their age and size after that the on- and off-cluster groups were compared for innovation input/output and annual financial performance. The results show that although there are more off-cluster firms than on-cluster, the innovation capabilities of on-cluster firms are much higher than off-cluster firms, and this effect was seen regardless of the age or size of the firms. At the aggregate level, the level of innovation exhibited by on-cluster firms is highly correlated with networking (expressed as outlay on social expenses), while R&D expenditure has more impact on innovation output (expressed as patents and licenses) for the off-cluster firms.

At the group level, on-cluster firms maintain a better financial performance up to age ~15, after that turnover starts to decline, and off-cluster firms over this age start to perform better. Next section recap on the data analysis technique used, then compares the entrepreneurship activities between on and off-cluster firm groups. Then, innovation activities are compared followed by firms' financial achievements, 4.6 explores the presence of spillover effect between the two groups, while section 4.7 concludes the chapter findings. This chapter is partially based on the writer's publication at the 19th European Conference on Knowledge Management (Al-kfairy et al., 2018).

4.2 Data analysis

After cleaning and categorising the data set, we summed up all the annual values for each category by applying Equation 3.1 in 3.5.3.

Table 4.1 shows a sample of the total values after executing (Equation 3.1). It shows that even though the number of firms outside the cluster is almost double that of the number of firms inside the cluster, the total number of employees for on-cluster firms outperform the off-cluster firms. For example, in 2008, there were 50 firms on-cluster and 120 firms off-cluster, but the 120 firms had only 424 employees compared to 606 employees on-cluster.

Table 4.1 Sample Data Generated Using Equation 3.1

Year	Total On-Cluster NOEs*	Total Off-cluster NOEs*	Total On-Cluster NOFs*	Total Off-Cluster NOFs*
2007	606	424	47	103
2008	686	513	50	120
2009	734	581	56	129
2010	757	669	56	144

***NOFs: Number of Firms *NOEs: Number of Employees**

Next, the growth rate in each category for firms for on- and off-cluster was calculated using natural logarithmic [natural logarithmic was proposed by many researchers, e.g. (Tavassoli and Tsagdis, 2014)] (equation 4.1):

$$GrowthRate(C) = (\ln(V(C,i) - \ln(V(C,i-1)) \times 100\%$$

Equation 4.1: Growth at Aggregate Level

After that, we calculated the mean values for each category to the number of firms (average per-firm), going on to apply the efficiency formula for averages per-firm (equations 4.1):

$$GrowthRate(Mc) = \ln(Vmean(C,i)) - \ln(Vmean(C,i-1)) \times 100\%$$

Equation 4.2: Growth at the Mean Level

Furthermore, Average growth rate was carried out for age groups (equations 4.3 and 4.4), and the average value for each of the firm sizes groups (equation 4.5). For the age groups, and since the firm can show up multiple times in the same age group, e.g. a firm can be in age group zero in 2007, 2008, 2009, then we calculated the growth rate per-firm using the equation 4.5. After that, we applied the average per-group (applying 5% trimmed mean technique for all groups to avoid the individual cases of outliers) to compare the results for on-and off-cluster firms:

$$GrowthRate(j,C) = (\frac{v_{tn}(c,j) - V_{t_0}(c,j)}{V_{t_0}(c,j)}) \times 100\%, \ if \ t_n \neq t_0 \ and \ t_0 \neq 0,$$
$$t_n \ is \ end \ of \ the \ period, \ and \ t_0 \ is \ the \ beginning \ of \ the \ period.$$

Equation 4.3: Growth Rate Per-firm

$$GrowthRate(mean,g) = (\frac{\sum_{j=1}^{n} GrowthRate(j,c)}{n}), n = \ number \ of \ firms \ in \ group,$$
$$g \ is \ the \ group \ based \ on \ firm \ ages.$$

Equation 4.4: Mean Growth Rate Per-firm

$$Average(C,m) = \frac{\frac{\sum_{i=0}^{t} v(c,j,i)}{t}}{n}, i \ year, \ where \ i = 0 \ is \ the \ start \ of \ the \ period,$$
$$and \ t = \ the \ end \ of \ the \ period, \ and \ n \ number \ of \ firms \ in \ size \ group \ m.$$

Equation 4.5: Average Value Per-size Group per Category

4.3 Entrepreneurship environment

One of the major goals of business clusters is to stimulate an entrepreneurial environment (Pitelis, 2012), which can be defined as building new businesses (Rocha, 2004). Here, entrepreneurship is measured using employment and firms' growth throughput using (equation 4.1), where the assumption is that each new firm is either created or moves into the area represents entrepreneurial activity.

Analyses show that entrepreneurial activity is higher off-cluster (Figure 4.1), e.g. between 2008 and 2015 firms' growth on-cluster was between (0% – 11%), while outside off-cluster was (7% – 23%). Employment growth shows similar results, where the average growth rate for the period in the off-cluster group was (12.06%), while it was (7.51%) for the on-clusters' firms' group.

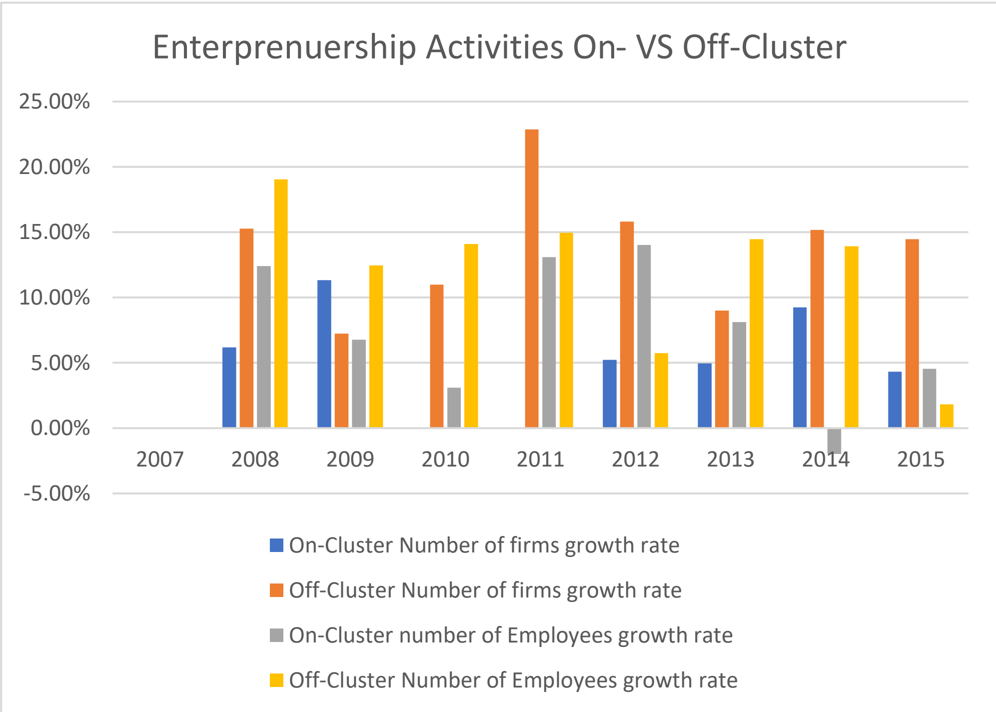

Figure 4.1 On- Vs Off-cluster Total Number of Firms and Employees' Growth Rate

On the other hand, the share of SMEs (small and medium enterprises) on-cluster is far higher than the off-cluster, which is characterised by being an environment consisting mainly of the micro firm (Table 4.2), which may imply that the chances of growing from micro to SME are higher on-cluster than off-cluster. Conversely, there being more SMEs on-cluster may equally be due to being grown with the cluster itself, i.e. mature clusters may include more mature firms; however, a firm can be counted twice if it was moved between different categories over time, e.g was micro in 2007, then it becomes medium on 2010.

Table 4.2 Firms Size Distribution

Emp Group	Total NOFs (On-Cluster)	Total NOFs (Off-Cluster)
Micro (0-9 Employees)	60	289
Small (10-49)	27	27
Medium (50-249)	16	12
Large (Larger than 250)	0	0
Not Reporting	0	59

4.4 Innovation capabilities

Previously, R&D expenditure has been used for measuring innovation and previous work reports a strong statistical correlation exists between R&D expenditure and net sales growth and firms' growth (García-Manjón and Romero-Merino, 2012). However, R&D usage is seen as sub-optimal because innovation takes a long time to start producing financial returns (Baptista and Swann, 1998; Lamperti et al., 2015). Patenting was also used as a metric of cluster innovation (Delgado et al., 2014; Squicciarini, 2008) and other factors, including social factors and networking (Morosini, 2004), and formal and informal networking channels (Bell, 2005) have been investigated. Lee et al. (2001) define innovation as activities which result in new processes or products and building on previous research (further discussion about innovation measurement methods is available in 2.5 and 2.4.5). Thus, we divide innovation indicators into input and output, where the input measured through R&D investment combined with networking using social expenses data, while the output is the return from selling/licensing patents and producing new products. This means that innovation is measured not only as patents but also through producing sellable products [see (Al-kfairy et al., 2017) and 2.5 and 2.4.5].

Table 4.3 shows that on-cluster firms spend a lot more on R&D and socialising than off-cluster firms up until (2013/2014). Knowing that off-cluster firms are dominated by micro firms, which may indicate that they are not product and research-oriented and could be, e.g. consulting companies. This speculation is supported by Figure 4.2, which in the time frame shown, illustrates that on-cluster firms produced a significantly higher innovation output than off-cluster ones. However, in 2013/2014, the off-cluster firms started to spend more on R&D and correspondingly produced a higher innovation output. Given this contradiction, SPSS 24 and Spearman correlation test were applied. The analysis shows that on-cluster innovation investment produced higher outputs than for off-cluster firms (R&D and Patents and License correlation coefficient is 0.6 and p-value= 0.088), however social expenses for on-cluster is (Rho = 0.683 and p-value = 0.042). For off-cluster firms' social expenses (networking) does not have a statistical significance correlation with patents a license (Rho=0.517 p-value = 0.154), while R&D have a higher impact than on-cluster (Rho = 0.733 and p-value = 0.25). This implies that firms on-cluster are more dependent on networking in producing innovation output, on the other hand, off-cluster firms are more dependent on R&D investments.

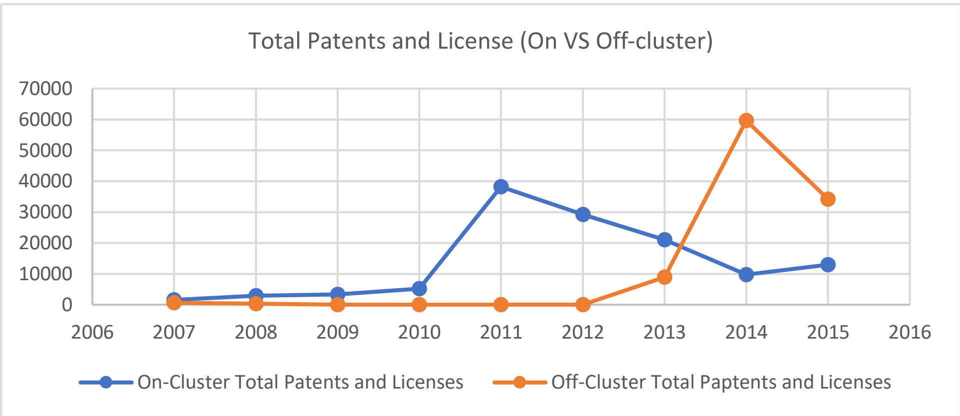

Figure 4.2 On- VS Off-cluster Total Patents and Licenses (KSEK)

Table 4.3 On- Vs Off-cluster Total R&D, Social Expenses and Patents and Licenses Income (KSEK)

Reporting Year	On-Cluster Total R&D	Off-Cluster Total R&D	On-Cluster Total Social Expenses	Off-Cluster Total Social Expenses	On-Cluster Total Patents and Licenses	Off-Cluster Total Patents and Licenses
2007	11,508	9,440	113,768	71,602	1,565	672
2008	29,283	16,419	134,969	100,365	2,913	308
2009	66,547	13,485	139,994	103,496	3,336	11
2010	79,618	4,199	146,059	131,324	5,191	0
2011	69,456	39,741	165,038	148,609	38,222	3
2012	116,919	45,477	191,125	159,132	29,202	71
2013	132,030	62,528	214,593	197,793	21,058	8929
2014	146,348	80,540	219,107	217,314	9,804	59652
2015	164,191	110,868	241,623	218,459	12,940	34179

Moving to compare age groups and firms' sizes innovation input/output. Table 4.4 presents the results obtained by applying equations 4.3 – 4.5. The results show that despite the age groups, the growth rate of (trimmed mean) for the off-cluster firms constant (zero). However, it is observable for the on-cluster firms there are some activities going on for patents growth (up and down), which indicates that on-cluster firms' concentrate more on such activates, similar results can be observed for R&D investments, however, when off-cluster firms become older (over than 20 years), then it starts to focus more on R&D investment.

Table 4.4 Average R&D and Patents and License (P&L) Growth Rate Per-age-group

Age Group	On-Cluster Firms R&D (average growth rate)	Off-Cluster Firms R&D (average growth rate)	On-Cluster Firms P&L (average growth rate)	Off-cluster Firms P&L (average growth rate)
Less than 5	0.47%	0.00%	0.00%	0.00%
Between 5 and 10	-5.70%	0.00%	25.11%	0.00%
between 10 and 15	1.98%	0.00%	-1.80%	0.00%
between 15 and 20	2.07%	0.00%	0.00%	0.00%
Over 20	27.84%	4.67%	-1.39%	0.00%

On the other hand, figure 4.3 displays the growth in social expenses (networking activities), from the figure, it is evident that from early stages of firm development, there are more social activates (presented) by the growth rate in the social activities, than off-cluster. However, as the firm grows this change, and starts to spend less (as the firms' network structure starts to shape).

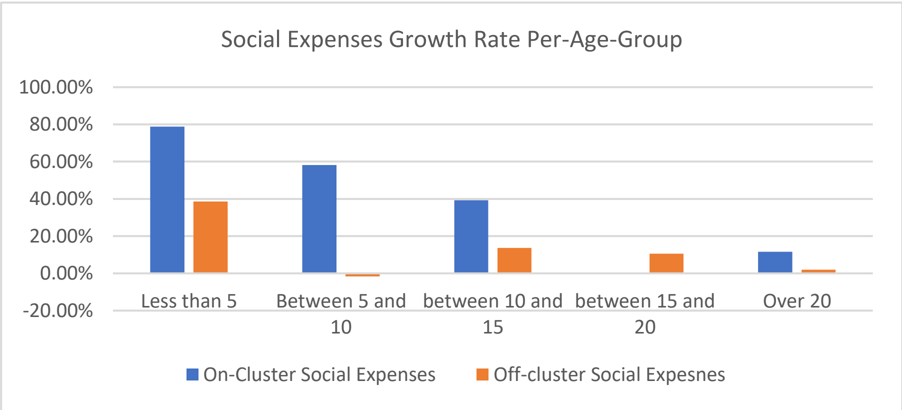

Figure 4.3 On- VS Off-cluster Average Growth Rate (social expenses) Per-age-group of firms

Moreover, similar results were obtained when comparing firm sizes groups, where on-cluster firms in average spend more (on R&D) when they are micro or medium than off-cluster firms, which confirms previous results of on-cluster firms being more innovation focus and therefore, more innovative than off-cluster firms (Table 4.5).

Table 4.5 Average R&D, Social Expenses (SE), and Patents and License (P&L) Income per-firm-size-group

Emp Group	Average On-Cluster Firms R&D (KSEK)	Average Off-Cluster Firms R&D (KSEK)	Average On-Cluster Firms SE (KSEK)	Average Off-cluster Firms SE (KSEK)	Average On-Cluster Firms P&L (KSEK)	Average Off-cluster Firms P&L (KSEK)
Micro (0-9 Employees)	52.82	0.73	444.07	157.86	1.56	0.00
Small (10-49)	411.96	742.07	3,483.65	4,144.80	23.44	1.28
Medium (50-249)	4,483.22	262.00	8,256.05	8,300.59	405.46	325.11

4.5 Financial situation

Financial outcomes were evaluated for both groups by analysing the average turnover per-firm. Turnover was selected over profitability because high-tech firms can take a long time to start generating profits (Folta et al., 2006), therefore turnover was taken as a more appropriate indicator of financial performance (see 2.4.5).

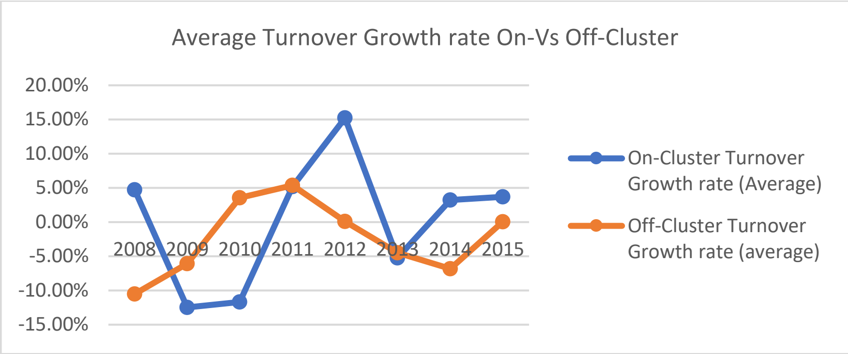

Figure 4.4 On- VS Off-Cluster Total Turnover Growth Rate

Figure 4.4 shows that on average on-cluster firms outperform off-cluster firms with regards to financial return. However, the growth rate was always changing, which does not show a stable line for both groups. Thus we used the actual observed average values (Table 4.6). It shows that both groups (on and off-cluster) has a stable average turnover, but, on-cluster firms show a better result in financial returns.

Table 4.6 Average Turnover (KSEK) Per-Firm

Reporting Year	On-Cluster (Average Turnover (KSEK))	Off-Cluster (Average Turnover (KSEK))
2007	22,775.96	9,735.18
2008	23,873.20	8,763.82
2009	21,073.68	8,245.69
2010	18,746.59	8,543.39
2011	19,741.80	9,015.02
2012	22,987.47	9,023.61
2013	21,815.71	8,627.04
2014	22,531.00	8,059.50
2015	23,382.39	8,062.51

Moreover, we have tested age groups as well as the firm sizes groups. It confirms earlier results presented in this section for firms with the age (0 – 15). Nevertheless, as on-cluster firms become older, then its turnover diminish, while the opposite applies to off-cluster firms. Moreover, we can notice that the average turnover is very closed in both groups regardless of the size group (Table 4.7).

In conclusion, we believe that, if a firm wants to generate more money through either selling products or attracting investors, it is better, to start on-cluster until a certain age (15 years old), then graduate into a different location.

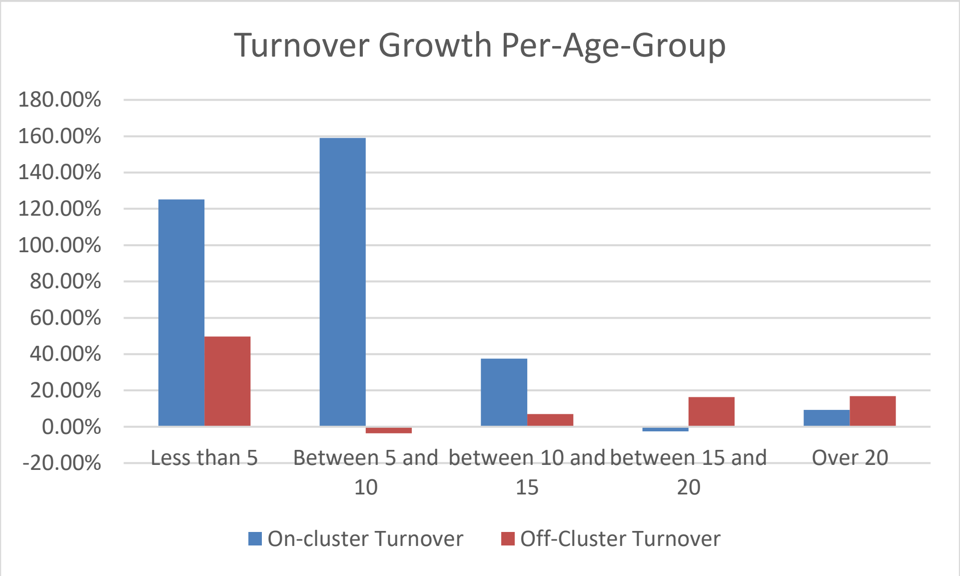

Figure 4.5 Turnover Growth Rate per-age Group

Table 4.7 Average Turnover Per Firms-size-group

Emp Group	On-Cluster Firms Average Turnover(KSEK)	Off-Cluster Firms Average Turnover (KSEK)
Micro (0-9 Emps)	3,177.22	1,359.51
Small (10-49 Emps)	23,753.86	28,665.25
Medium (50-249 Emps)	56,466.75	50,920.77

4.6 On-cluster and off-cluster spillover

Previous sections compared the performance – at the aggregate level- between firms located on cluster and firms located out of the cluster. However, in our case, firms are located in the same city, where on-cluster firms are being mainly distinguished by being connected to a central organisation. Therefore, the borders between on- and off-cluster firms are skinny, which means that it is possible to achieve employees as well as ideas (innovation) mobility between the two groups. Previously, the spillover effect between different clusters was investigated (Delgado et al., 2014), which investigated the relationships between clusters of similar and related industries in the same regions. They reported that growth in one cluster would typically result in a growth for clusters of related industries in the same region. Thus, in this section, we explore group performance correlation called spillover effect between on- and off-cluster firms.

First, we will explore if there is any relationship between the two group sizes using the number of employees and firms. Table 4.8 shows a strong positive correlation (using Pearson correlation) between On- and Off-cluster number of firms and employees. On the other hand, these results were obtained using absolute values, which means it does not tell the whole story. Thus, we checked for any correlation in the growth rate in the number of firms and employees on- and off-cluster by first applying equation 3.2, then run Pearson correlation. The analysis shows no correlation between the growth on- and off-cluster (table 4.9), which contradicts the previous results. This implies that an increase in the number of firms and employees inside the cluster would not result in an increase off-cluster, indicating that if a cluster entrepreneurship environment prospers, this stays inside the cluster and will not impact the group (aggregate) firms located around that cluster, even with very close proximity. Moreover, this means that if a cluster includes incubator, then firms – most likely- will graduate into inside the cluster or cluster firms' spin-offs occurs inside the cluster. However, these hypothesise will need further investigation, which we will leave for future research.

Table 4.8 Correlation Matrix for On - and Off-Cluster Number of Employees, and Number of Firms

	On-Cluster Number of Employees	On-Cluster Number of Firms
Off-cluster Number of Employees	0.969 (P-Value less than 0.001)	-
Off-Cluster Number of Firms	-	0.959 (P-Value less than 0.001)

Table 4.9 Correlation Matrix: Growth Rate in Number of Employees and Number of Firms On- and Off-Cluster

	On-Cluster NOEs Growth	On-Cluster NOFs Growth
Off-cluster NOEs Growth	0.066 (0.876)	
Off-Cluster NOFs Growth		-0.487 (0.221)

Second, previous sections highlighted that one of the most important characteristics of a business cluster is the innovation capabilities, where it is stimulated through networking between firms and personals (formal and informal channels). However, off-cluster firms are located in close proximity, which increases the possibilities of cooperations between firms and/or friendship connections. In order to investigate this, we checked for any correlation between the produced innovation using the total value of patents on- and off-cluster, as well as the growth rate in these values. The results present no correlation between the total value of patents on- and off-cluster with correlation coefficient (- 0.097, p-value = 0.805). Furthermore, similar results were obtained when evaluating the relationship between Patens values growth on- and off-cluster (-0.635, p-value = 0.175). This indicates that there is no spillover effect between on- and off-cluster firms with regards to innovation output, which means innovation occurs inside the business cluster stay inside the cluster even with very close proximity.

In conclusion, these results show that the cluster will keep its identity and might not have any impact on firms in the surrounding areas. So, statistically firms' creation process inside the cluster (spin-offs, incubator programmes, and entrepreneurial inside the cluster), would not impact the closed surrounding area, and it will be – only – inside the cluster. Moreover, the same applies for innovation, although, it is possible to have a formal and informal connection between firms on- and off-cluster especially with closed proximity, this does not result on knowledge, and innovation spill-over. However, these results were based on a statistical analysis of one case, which may cause a bias to the case. Therefore we believe that further check is needed by using more cases and having a closer look into the micro-level (single firm cases).

4.7 Conclusion

Results show that by constructing a science park, the entrepreneurial environment is stimulated both on- and off-cluster. In this case, the total number of employees on-cluster was approximately triple of that off-cluster. These results for a mature (over 33 years old) cluster are consistent with earlier results (Tavassoli and Tsagdis, 2014). The preponderance of SMEs on-cluster may indicate that mature clusters are inhabited by firms that have passed the incubation period, although this hypothesis needs further investigation.

The growth in the number of on-cluster firms is not high, which could be the result of simple factors like the availability of space (congestion effect), or whether the mature cluster can foster more business creation on-cluster or other factors, and thus remains an open question.

Inhabiting a cluster appears to correlate with innovation input and the resultant output, certainly investing in R&D and socialising on-cluster appears related to more innovation, supporting the previous report by (Lamperti et al., 2015). However, the data did not enable us to check if firms located off-cluster are less product and research-oriented than on-cluster ones, and this may be one future research question. These results were confirmed by firms' size distribution and age distribution. It means that regardless of firm size or age, it is better for product/patents oriented firms to locate on cluster than off-cluster, albeit that the results show a decline in patents and license growth after 2013, but this can be related to this specific cluster effect (unobserved parameters), which can a future research question.

On-clusters firms showed better turnover than off-clusters firms. However, off-cluster firms exhibited a better turnover growth for firms older than 15 years, regardless of the firm size, which might imply that on-cluster firms should graduate from it when it arrives into a certain age and growth rate (of course dependent of the firm type).

Thus, this study implies that a successful and mature cluster can generally add to the regional performance and economic stability. Specifically, a cluster can foster more innovation within the cluster firms albeit that some factors like the delay between innovation production and financial returns, means that this might not result in better financial returns in the short-term.

Moreover, we checked for any spillover effect occurring between the on- and off-cluster firms, primarily because of the soft borders between the two groups. The results prove that there is not any connection between the development on- and off-cluster. Indicating that any development inside the business cluster will not impact the surrounding areas and visa-versa. However, this study identified and many directions which can extend into the current knowledge of MSP efficiency and general knowledge of business cluster, which will be further discussed in the future research section of the conclusion chapter.

Chapter 5: Modelling Business Cluster Success Factors

5.1 Introduction

This chapter builds the actual econometric models. It starts by discussing the method used for constructing the models, by introducing all technical steps, then moves to model the business cluster success indicators at the aggregate and micro-level using MSP case study. This chapter aims at exploring different models to find the best-fit model, which leads to extract success factors at both aggregate and micro-level.

This chapter illustrates that, at the aggregate level, business clusters size can be modelled using its age, which is the way to model the cluster number of firms. Then, from a number of firms, it is possible to extract the expected number of employees. After that, it emphasises the importance of firms networking by modelling firms' innovation capabilities using social expenditure, moving on to build a more comprehensive view by modelling the cluster financial returns using cluster number of firms. This underlies the cluster maturity importance as well as the importance of the entrepreneurship environment in sustaining business cluster development.

Then, at the micro-level, results emphasise the importance of continuous innovation in sustaining firms' growth both financially and in size. It illustrates that shareholders investment will contribute into firm's growth linearly, while firms' maturity measured as the firms' age since establishment has a complicated relationship (nonlinear) with both employment growth as well as financial growth. While networking contributes to better innovation outcome.

The chapter starts by discussing the methodology used for building econometric models in section 1, section 2 builds the cluster size models using the number of firms and number of employees, then cluster innovation capabilities econometrics model is constructed in section 3. Section 4 discusses the cluster financial capabilities, and section 5 concludes. This chapter is partially built from the author's publications [see (Al-kfairy et al., 2019a; Al-Kfairy et al., 2017)].

5.2 Methodology

This section will go through the methodology used to extract business cluster success factors from the identified indicators on the conceptual model (chapter 3). It starts by discussing the method used for the aggregate level, then the micro-level. Thus, the next section provides insight into the methodology used at the aggregate level analysis.

5.2.1 Aggregate level methodology

In this chapter, we started by summing up all categories of concern as described in chapter 3, equation 3.1. Then, we modelled each of the following categories:

1. Number of Firms: for modelling entrepreneurship (size of cluster) (5.3.1).
2. Number of employees: for modelling entrepreneurship (Size of the cluster) (5.3.1).
3. Accumulative patents and licenses values (for modelling innovation capabilities) (5.3.2).
4. Turnover: for modelling financial situation (5.3.3).

After that, models of cluster success indicators at the micro-level were constructed. Next section discusses the methodology used for building econometric models at the micro-level.

5.2.2 Micro-level methodology

Panel data analysis techniques, with fixed and random effects, were used with off-cluster firms as a control group. Panel data analysis was previously used in identifying if on-cluster firms are more innovative than off-cluster firms with industrial and individual fixed effect (Baptista and Swann, 1998), and cluster industrial innovation growth (Delgado et al., 2014; Delgado et al., 2010). Earlier studies highlight the advantages of using Panel data analysis, which can be summarised as it builds better inference models due to its high degree of freedom. It helps in building and tests more complex models (than normal linear regression models), helps controlling for the variables which are not part of the model, help in reducing collinearity between different model variable, which makes it more dynamic than, e.g. time series models [see (Hsiao, 2007)].

A longitudinal dataset for the years 2007 – 2015 of firms using industrial code "62X" (programming and related industries) was collected from Swedish companies' database "ratsit" for all companies located in Linköping municipality (Klofsten et al., 2015). Firms were divided into two groups (on-cluster and off-cluster), as described in 3.5.2 and 3.5.3.

Panel data regression was applied for evaluating the variables contributing towards the financial and employment growth of firms as well as their innovation capabilities using Stata 14 statistical software package. The resulting models obtained were checked against the off-cluster group to understand if there are any differences in the success indicators on- and off-cluster. The Hausman test was applied to select between fixed and random effect models, as well as tests for time fixed effect. The following steps were followed for running regression analyses:

1. The on-cluster dataset was loaded into Stata.
2. A unique identifier was set using the organisation number and the time (year) of the data point.

3. The associated number of employees and turnover were transformed using the natural logarithmic functions (ln(x), where x = the number of employees or turnover).

4. As previously (Diez-Vial and Fernández-Olmos, 2017) the total value of the variable “patents ratio to the turnover” was used to represent innovation

5. The models were built using Stata, where both linear and quadratic models were tested. Variables were added one by one, and, as before (Torres-Reyna, 2007) p-values were derived each time a new variable was added. The selection of the best fit model was based on trial and error methodology using a number of factors which are summarised as follows:
    a. Previously identified in the literature as being of possible interest.

    b. Variables were added individually and either accepted as part of the model or rejected, based on its p-value, where (p-value > 0.05) is rejected.

    c. Variables were tested using both linear and quadratic models using both the overall generated p-values and R^2-adjusted values. If the p-value is significantly improved using the quadratic model (e.g. being rejected with the linear model and reporting a p-value > 0.05 while quadratic model reported a better p-value <0.05, which means it was statistically insignificant with the linear model and becomes statistically significant with quadratic model), then the quadratic model is used. Otherwise, if (p-value < 0.05) and R^2-adjusted value was not significantly improved then linear models are assessed: Both the overall model p-value and the coefficient p-value, and evaluate both of them, as both must be less than the cut-off point of 0.05.

6. The Hausman test was used to select between fixed and random effect models.

7. We tested for time fixed effect as previously described by (Torres-Reyna, 2007).

8. Steps 2-5 were repeated for the off-cluster firms, and if significant p-values were found, then steps 6 and 7 were also applied.

Previous steps help to identify the actual factors influencing firms' development at the micro-level for both on- and off-cluster firms. It leads to finding the actual factors influencing firms' development at the micro-level for both on- and off-cluster firms, which is then used to extract the needed policies.

5.3 Success factors models at aggregate Level

5.3.1 Business cluster size model (aggregate level)

Entrepreneurship is one of the mean goals of building business clusters (Pitelis, 2012). Typically, they are built at the vision of enhancing the right environment to encourage entrepreneurially. Therefore, entrepreneurship is believed as one of the main success indicators of business clusters. However, as there are many definitions of entrepreneurship, which influence the method of measuring it, we instead model the size of the cluster using the number of firms and employees over time.

Table 5.1 presents the number of firms and employees in MSP, as reported by the identified sources in

Table 3.3. Null means that the data point was not reported.

Table 5.1 MSP Number of Employees and Number of Firms

(as Reported in Literature)

Year	Cluster Age	Total Cluster NOFs	Total Cluster NOEs
1984	1	6	150
1988	5	18	300
1992	9	49	1000
1994	11	NULL	1400
1996	13	110	3000
1998	15	115	4300
2000	17	150	5500
2002	19	170	4500
2004	21	NULL	4000
2005	22	210	NULL
2006	23	228	4700
2007	24	230	5800
2008	25	NULL	6000
2009	26	NULL	5950
2010	27	NULL	6050
2011	28	260	6100

***NOFs= Number of Firms**

***NOEs = Number of Employees**

Using SPSS, we first run linear correlation analysis between age, the number of firms and number of employees (Table 5.2), which proves that all parameters are highly correlated at the statistical significance of over 99% (p-values are less than 0.001).

Thus, we use natural logarithmic data transformation to compute the growth of each variable ($\ln(c)$, $where\ c\ is\ either\ NOFs\ or\ NOEs$)[15].

Table 5.2 Pearson Correlation Matrix

(Cluster Age and Number of Firms in the cluster)

	Cluster Age	**Number of Firms**
Number of Employees	0.946**	0.935**
Cluster Age	-	0.991**

**** Statistically significant at more than 99%**

Then, we run linear and quadratic regression for ln ($NOFs$) using cluster age as predictor together with Analysis of Variance (ANOVA analysis) to obtain the best fit model, where linear model reported *R^2-adjusted = 0.877, and p-value less than 0.001* (ANOVA), while the quadratic model disclosed *R^2-adjusted = 0.994, and p-value less than 0.001*, with a better curve fit for the quadratic model (Figure 5.1). Therefore, the quadratic model was selected.

[15] See the following discussion about using natural logarithmic in econometrics modelling https://stats.stackexchange.com/questions/27682/what-is-the-reason-why-we-use-natural-logarithm-ln-rather-than-log-to-base-10

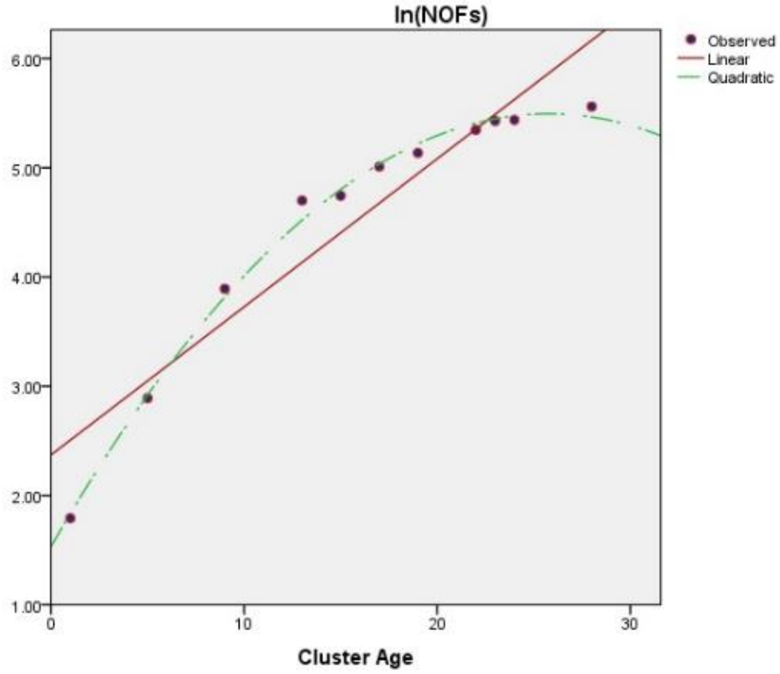

Figure 5.1 Curve Estimation for Cluster Age VS Total Clsueter NOFs

Table 5.3 provided the coefficient variables applied to the quadratic model. It concludes that the obtained models are very strong, as all the reported p-values are less than 0.001 (0.00).

Table 5.3 Cluster NOFs Model using Quadratic Model and Cluster Age

Coefficients				
	Unstandardized Coefficients	Standardized Coefficients	t	Sig.

	B	Std. Error	Beta		
Cluster Age	0.307	0.013	2.139	23.586	0.000
Cluster Age ^{2}	-0.006	0.000	-1.239	-13.665	0.000
(Constant)	1.532	0.087		17.648	0.000

After that, we applied linear and quadratic regression between cluster age and natural logarithmic of the number of employees inside a cluster as the correlation analysis shows a strong relationship between the number of employees and cluster age than the number of employees and number of firms (with very little absolute difference). Again, based on the R^2-adjusted and the curve estimation, we preferred the quadratic model over the linear model with R^2-adjusted of *0.811* for linear and *0.964* for the quadratic model (applying ANOVA analysis as well). Moreover, we tested the relationship between the number of firms and the natural logarithm of the number of employees, which shows better results than cluster age when running quadratic regression with *R^2-adjusted = 0.967*. Thus, we selected the number of firms quadratic model as a predictor for the number of employees albeit that there is a very strong correlation between the number of firms and cluster age indicating that these two predictor variables are replaceable, but colinear (Table 5.4 and Figure 5.2).

Table 5.4 Quadratic Model for NOEs using NOFs

Coefficients					
	Unstandardized Coefficients		Standardised Coefficients	T	Sig.
	B	Std. Error	Beta		
Number of Firms	0.038	0.003	2.550	11.065	0.000
Number of Firms^2	-9.545E-05	0.000	-1.738	-7.542	0.000
(Constant)	5.023	0.189		26.578	0.000

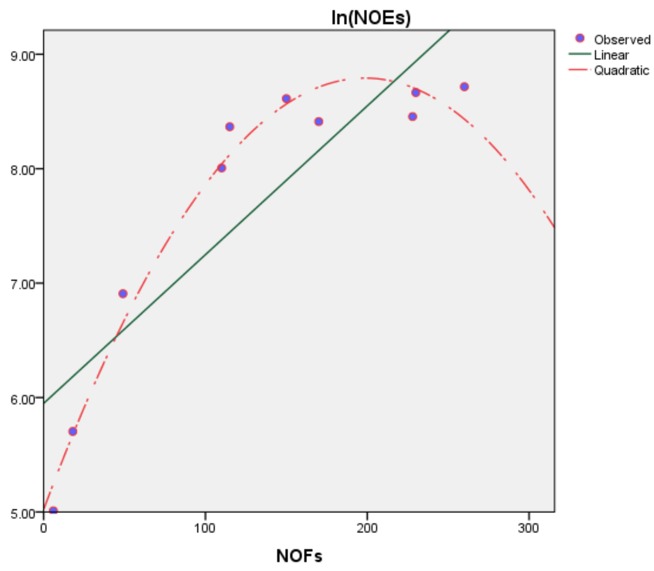

Figure 5.2 Cluster NOEs Regression Models Using Cluster NOFs (Linear and Quadratic)

Previous models prove the crucial role that the cluster age plays in identifying the nature of development inside business clusters. It shows that business cluster development (in term of size) is not linear, which follows the lifecycle hypothesis [see (Sonderegger and Täube, 2010; Menzel and Fornahl, 2009; Martin and Sunley, 2011)] of different development stages. Moreover, these models help in obtaining optimal cluster age, the number of firms, which are approximately 200 firms and 20 years old of the business cluster, however, these optimal values may be different when controlling for other factors. After understanding how is the size of business clusters can be evaluated, we move on to understand the factors that influence business clusters innovation in the next section.

5.3.2 Business cluster innovation capabilities models

The previous section discussed the cluster capacity and how it can be modelled. However, as a business cluster is built to stimulate innovation in its region, then one of the most important success indicators is being able to produce more innovation. Therefore, based on our conceptual model, we will take a closer look at the cluster aggregate level of innovation. We will use the accumulated book value of patents as an indicator of innovation, following on Porter suggestion on using the number of patents (Porter, 2000). However, we use the actual value, which can be a potential income at some point. Therefore, using equation 3.1, we constructed table 5.5.

Table 5.5 Innovation Data at Cluster Aggregate Level

Year	Total Firms R&D	Total Firms Social Expenses	Total Number of Employees (Cluster Size)	Average Firms Ages	Total Value of Patents (Cluster Firms)
2007	11,508	113,768	606	8.787234	1,565
2008	29,283	134,969	686	9.36	2,913
2009	66,547	139,994	734	9.428571	3,336
2010	79,618	146,059	757	10.42857	5,191
2011	69,456	165,038	863	11.07143	38,222
2012	11,6919	191,125	993	11.49153	29,202
2013	132,030	214,593	1077	12.1129	21,058
2014	146,348	219,107	1056	12.19118	9,804
2015	164,191	241,623	1105	12.4507	12,940

Using the correlation analysis applied in 4.4, we applied regression analysis for the natural logarithmic of patents and licenses with both R&D and social expenses using SPSS and both linear and quadratic models. The regression models suggested a better fit by using social expenses as predictor rather than R&D with R^2*-adjusted = 0.386*, and *p-value = 0.044*, while when using R&D we got R^2*-adjusted = 0.340*, and *p-value = 0.058*. Moreover, we selected the linear model rather than the quadratic model due to bad reported p-values and coefficient for the quadratic models (tables 5.6 and 5.7).

Table 5.6 Quadratic Model of Cluster Innovation Using Social Expenses

Coefficients					
	Unstandardized Coefficients		Standardised Coefficients	T	Sig.
	B	Std. Error	Beta		
Total Social Expenses	0.000	0.000	6.906	3.340	0.016
Total Social Expenses ^{2}	-4.391E-10	0.000	-6.252		
(Constant)	-7.097	4.438		-1.599	0.161

Table 5.7 Linear Model of Cluster Innovation Using Social Expenses

Coefficients					
	Unstandardized Coefficients		Standardised Coefficients	T	Sig.
	B	Std. Error	Beta		
Total Social Expenses	1.709E-05	0.000	0.680	2.454	0.044
(Constant)	6.075	1.247		4.872	0.002

Above results show a moderate impact for both R&D and Social expenses on clusters' innovation capabilities. However, it provided a better fit when using social expenses as the model predictor. Moreover, we neglected using both R&D and Social expenses in a multilinear model to avoid collinearity as both R&D and Social expenses are highly correlated with *correlation coefficient = 0.971 and p-value = less than 0.001*. On the other hand, we could not find any significant relationship between book value of patents and license with group contribution, average firm age, and shareholders contributions with p-values of 0.587, 0.130, 0,179 respectively indicating that networking and socializing is the main determinant of business clusters innovation, which confirms earlier results obtained in 4.4. The nature of the linear positive model suggests that the more you network inside a business cluster, the more you are expected to innovation.

However, this conclusion will be revisited in the next section when modelling at the micro-level. On the other hand, this underlines the importance of Social expenses and networking in general (see 2.4.5 and 2.5). Consequently, we checked the factor which influences the networking expenses, and mainly the size factor (Which is related to DI number suggested in Mellor,2015), which reports a very high correlation with both number of firms and number of employees with correlation coefficient of 0.927 and 0.986 respectively suggesting that number of employees is the main determinant. Thus, we build a regression model for it, using the number of employees (figure 5.3).

This section illustrates that innovation capabilities at cluster level are mainly effected by socialising, which is a confirmation of earlier studies that networking is one of the most important clusters' factors and the main reason for firms to locate inside a cluster (see sections 2.5 and 2.4.5). It is also considered as the main difference between firms located on and off-cluster (section 4.4). Next, we will go through the factors which influence clusters' financial situation.

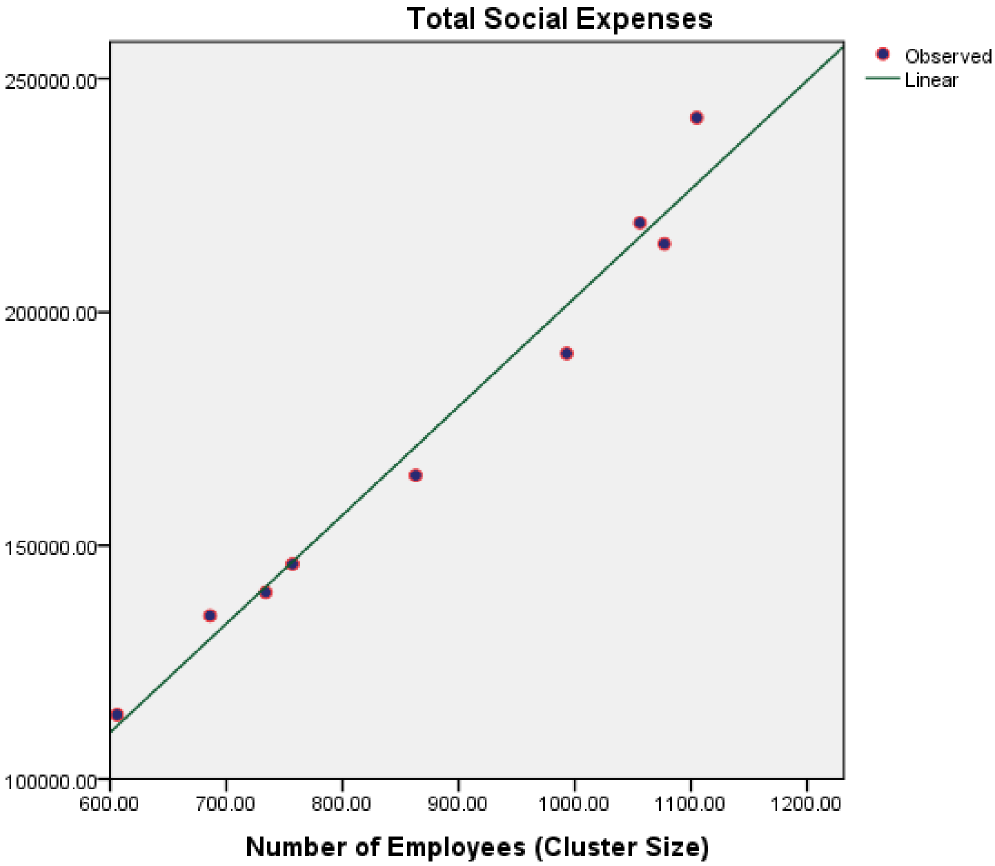

Figure 5.3 Modeling Cluster Number of Employees VS Cluster Social Expenses

5.3.3 Business cluster financial return models

Following on the conceptual model presented in 3.3.1, we moved into modelling financial return using turnover data, the reason for selecting turnover over profitability is (as mentioned in 2.4.5) are because of the nature of the firms located in MSP, which are technology-based firms. Typically, such firms would need some time to start producing a profit, as it is investing in building its products in the first few years (s). Thus, we start by running a Pearson correlation analysis against all the available parameters.

Table 5.8 Correlation Matrix: Turnover (Aggregate Level, On-cluster)

	Total Firms Turnover	
	Pearson Correlation	p-value
Total Firms Group Contributions	-0.371	0.326
Total Firms R&D	0.891	0.001
Total Firms Patents and License	0.297	0.438
Total Firms Shareholders Contribution	-0.320	0.401
Total Firms Number of Employees	0.846	0.004
Total Firms Social Expenses	0.865	0.003
Total Cluster Number of Firms	0.958	0.000
Average Cluster Firms Age	0.843	0.004

It is clear from table 5.8 that size is the most important factor influencing the total turnover. Therefore, we will consider one of the size parameters, and not both of them to avoid collinearity problem. However, the total number of firms provides a higher correlation coefficient than the number of employees. Thus, it is selected as the first parameter for the regression model, then we checked the correlation between other matrices (Social Expenses and R&D), and number of firms, which shows a very high correlation between each of the three variables (Table 5.9), thus NOFs was selected as a predictor for Total Turnover.

Table 5.9 Correlation Between R&D, Social Expenses and NOFs (on-cluster)

Correlations				
		Total Firms R&D	Total Firms Total Social Expenses	NOF
Total Firms R&D	Pearson Correlation	1	0.971**	0.961**
	Sig. (2-tailed)		0.000	0.000
Total Firms Total Social Expenses	Pearson Correlation	0.971**	1	0.927**
	Sig. (2-tailed)	0.000		0.000
**** Correlation is significant at the 0.01 level (2-tailed).**				

Thus, we tested both linear and quadratic regression for natural logarithmic of the total Turnover using the NOFs, which reported an R^2-adjusted = 0.814 for linear VS 0.881 for quadratic with better p-values for the linear model, therefore linear model was used (Table 5.10). This suggests that the financial return of business cluster must be linearly correlated with its size (number of employees and firms as they are both correlated), meaning that the more firms you have on-cluster, the more it is expected to generate money either through selling products or through raising funds with the help of CIs. If this is not the case, then there is a very high chance for the cluster to lose firms and therefore close.

Table 5.10 Linear Model for Total Cluster Firms Turnover using NOF (On-cluster)

Coefficients					
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
NOFs	0.028	0.005	0.915	6.009	0.001
(Constant)	12.738	0.331		38.457	0.000

5.3.4 Discussion

Previous sections build a different model for quantitively evaluate business cluster performance. Statistical models were built using a longitudinal data set and are based at the aggregate level (using equation 3.1). The obtained models prove that cluster size and age are the most important factors influencing cluster development. Therefore, cluster managers must pay more attention to these factors. Moreover, the cluster development model is well-aligned with cluster life cycle models [see (Martin and Sunley, 2011; Menzel and Fornahl, 2009)], which shows a cluster might still behave well and – at the same time - move through different development stages.

However, these models were based on evaluating the aggregate level of business clusters, which can be biased into a particular case when having few numbers of data points (as in our case), and there are no more data for testing the models. Thus, we consider this model (untested) as a baseline for further future studies. Moreover, it acts as a baseline for modelling firms' performance at the micro-level. On the other hand, these models must be tested (as future work), taking into account both simultaneity and endogeneity bias.

5.4 Success factors models at the micro-level

After modelling business cluster performance at the aggregate level (as a group), it is crucial to understand how firms would behave inside the cluster since the model at an aggregate level might be biased due to having only 8 years data. This will help policymakers, and firms' managers specify the firms' needs inside the cluster. In order to do that, we used Stata statistical package version SE 14.

This section evaluates the different dimensions of firms' performance (similar to cluster performance dimensions and the aggregate level analysis in previous sections) using panel data analysis techniques (with fixed and random effects) and off-cluster firms as a control group. Panel data analysis was used to investigate factors influencing the growth for on-cluster firms using off-cluster firms as a control group. Findings highlight that size and age influence turnover, as does the ability to innovate, but whereas size and age have a non-linear impact on financial growth, innovation capabilities have a positive linear impact. Employment is mainly correlated to age, the previous years' innovation and shareholder investment. Innovation output, (the ratio of patents asset value to turnover) is correlated to networking measured as social expenditure, which in turn exhibits a positive influence on innovation capabilities.

This section starts by constructing the model to predict the growth rate in the number of employees (size of the firm), then we assess the financial behaviour of firms and which factors influence it. After that, we look at innovation capabilities and the main factors affecting innovation at firms' level. Next model policy implications are discussed followed by chapter findings remarks.

5.4.1 Firms employment growth

The growth of the firm was evaluated against firms age, innovation output, shareholders investments and (in term of group investment), group contributions. Both linear and quadratic regressions using the absolute values, the final equation is shown as Equation 5.1:

$$ln(emp_{i,t}) = B_1 \times Age^2_{i,t} + B_2 \times Age_{i,t} + B_3 \times Innov_{i,t-1} + B_4 \times SC_{i,t-1} + U_i + C$$

Equation 5.1: Firms Employment Growth Regression (prediction) Model for On-Cluster Firms

Where Age is the firm age at the time of assessment, *SC* is the shareholders' contributions in the previous year (*t-1*), U_i is firms' specific effect, and *Innov* is the previous year innovation calculated as the following:

$$Innov_{i,t} = \frac{TPV_{i,t}}{Turnover_{i,t}}$$

Equation 5.2: Innovation Indicator Equation

and (Equation 5.2) where *TPV* = the total book value of patents of firm *i*, in the year (*t*).

Then, the Hausman test was applied to decide if a random effect is more appropriate than the fixed effect because this has previously been found (Torres-Reyna, 2007) to be good practice. The test reported (chi^2 = 0.2728, failure to reject the null hypothesis), which indicates that the random effect model must be used. The Breusch and Pagan Lagrangian multiplier test were applied for random effects vs OLS regression, which reports (Prob > chi^2 = 0.0000, rejecting the null hypothesis), and conclude that random effect is the most appropriate model. This indicates that there are no correlations between the independent variables (Age, Innova, and SC) with individual-specific effect (each organisation is different from each other with a factor of U_i relative to the first organisation). The model reported a U_i between minimum = -2.181455, and maximum = 2.759062. This means that the effect on employment growth in individual firms can be either negative or positive and that this is specific to each organisation. Values were obtained by running different regressions, which reports (almost) the same coefficient, thus we used the R^2 = 91%, and R^2-adjusted = 89% as given by the OLS regression.

Table 5.11 The Employment Growth for On-cluster Firms (Fixed VS Random Effects)

Parameter	Fixed Effect Coefficient(p-value)	Random Effect Coefficient (p-value)
B1 ($Age_{i,t}$)^2	- 0.002864 (0.000)	- 0.002580 (0.000)
B2 ($Age_{i,t}$)	0.118949 (0.000)	0.116393 (0.000)
B3 ($Innov_{i,t-1}$)	0.014658 (0.009)	0.146333 (0.009)
B4 ($SC_{i,t-1}$)	0.000071 (0.009)	0.000068 (0.011)
Constant	1.166648 (0.000)	1.007337 (0.000)

Table 5.11 presents the values of the coefficients and shows a positive correlation (linear) between last year innovation output and employment growth and similarly between previous year shareholders contributions and employment growth. However, the model presents a more complex (quadratic) relationship between firms' ages and employment growth.

Table 5.12 The Employment Growth for Off-cluster Firms Obtained by Applying Equation 5.1

Parameter	Fixed Effect Coefficient (p-value)	Random Effect Coefficient (p-value)
B1 ($Age_{i,t}$)^2	0.000052 (0.881)	- 0.000019 (0.954)
B2 ($Age_{i,t}$)	0.005044 (0.603)	0.010581 (0.244)
B3 ($Innov_{i,t-1}$)	0.014658 (0.320)	0.229880 (0.311)
B4 ($SC_{i,t-1}$)	0.333071 (0.005)	0.000017 (0.001)
Constant	1.056962 (0.000)	0.922160 (0.000)

Table 5.12 shows that for off-cluster firms, in contrast to on-cluster firms, almost all p-values were higher than cut-off point p-value (0.05) in both fixed and random effect models. *Shareholder contributions* (*SC*) exhibited a correlation, but interestingly *Innov* did not, showing that *Innov* is a correlating factor in on-cluster firms but not in off-cluster (compare Tables 5.11 and 5.12). In order to investigate the actual difference between on- and off-cluster firms in this respect, good p-values were taken and Equation 5.3 was used.

$$ln(emp_{i,t}) = B_1 \times Age_{i,t} + B2 \times SC_{i,t} + B_3 \times SES_{i,t-1} + U_i + C$$

Equation 5.3: Employment Growth Regression Model (Off-Cluster Firms)

Where *SC* is the shareholders' contribution for the firm (*i*) in the year (*t*), *SES* is the social expenses score for the firm (*i*), in the previous year (*t-1*), and *Age* is the age (years since founding) of the firm. Hausman test concluded that random effect is the most appropriate, and the preference is to use the random effect model over OLS regression. This resulted in the coefficient B_1= 0.008154, B_2= 0 .000011, and B_3 = -0.006861. These results mean firstly that for the off-cluster firms, as the firm ages, it employs more people, and similarly is the shareholders contribution (*SC*). However, the socializing score has a negative impact, meaning that the more social expenditure has been in the previous year, the lower the expected growth the year after.

5.4.2 Firms financial growth

To model the factors influencing financial growth rates, the procedure defined in 5.2.2, was generally followed, applying Equation 5.4:

$$ln(Turnover_{i,t}) = B_1 \times Emp_{i,t}^2 + B_2 \times Emp_{i,t} + B_3 \times Age_{i,t}^2 + B_4 \times Age + B_5 \times Innov_{i,t-1} +$$
$$B_6 \times Innov_{i,t} + B_7 \times ln(R \& D_{i,t-1}) + U_i + C$$

Equation 5.4: Financial Growth Regression Model (On-Cluster)

The Hausman test results were (Prob>chi^2 = 0.0242) indicating that the fixed effect model is the one to use (table 5.13). When the fixed effect of time fixed was investigated, the result was (Prob > F = 0.8970) indicating an absence of time fixed effect. Therefore, we only generated the individual fixed effect (U_i), which generated values between minimum = -4.9, and maximum= 2.7.

Table 5.13 The Financial Growth of On-cluster firms,

(Random VS fixed Effect)

Parameter	Fixed Effect Coefficient(p-value)	Random Effect Coefficient(p-value)
B1 ($Emps_{i,t}$)^2	- 0.000204 (0.000)	- 0.000294 (0.000)
B2 ($Emps_{i,t}$)	0.051895 (0.000)	0.075572 (0.000)
B3 ($Age_{i,t}$) ^{2}	- 0.002714 (0.052)	- 0.002299 (0.066)
B4 ($Age_{i,t}$)	0.087002 (0.032)	0.069730 (0.050)
B5 ($Innov_{i,t-1}$)	0.025648 (0.015)	0.022256 (0.032)
B6 ($Innov_{i,t}$)	- 0.118195 (0.001)	- 0.121068 (0.000)
B7 (ln($R\&D_{i,t-1}$))	0.055262 (0.019)	0.049959 (0.026)
Constant	7.415426 (0.000)	7.056322 (0.000)

Table 5.13 summarizes the relationship between firms' financial growth and size, age and innovation. It shows a positive correlation and effect of innovation (measured as a value of patents to turnover) in the previous year (*t-1*) with financial growth, where R^2 = 87%, and R^2-adjusted = 85%, again indicating a strong fit.

As before, for off-cluster firms, poor p-values were found for some of the parameters using both random and fixed effect models, possibly indicative of differences in the effect of factors between on-and off-cluster firms (see table 5.14).

Table 5.14 Off-cluster Firms' Financial Growth
(random and fixed effect) Applying the Model Obtained From Equation 5.4

Parameter	Fixed Effect Coefficient(p-value)	Random Effect Coefficient(p-value)
B1 ($Emps_{i,t}$)^2	- 0.000787 (0.000)	- 0.001049 (0.000)
B2 ($Emps_{i,t}$)	0.128826 (0.000)	0.163186 (0.000)
B3 ($Age_{i,t}$)^2	0.001131 (0.204)	0.000663 (0.413)
B4 ($Age_{i,t}$)	- 0.050358 (0.042)	- 0.033691 (0.119)
B5 ($Innov_{i,t-1}$)	- 0.872358 (0.803)	0.505128 (0.436)
B6 ($Innov_{i,t}$)	1.303690 (0.747)	1.537478 (0.490)
B7 (ln($R\&D_{i,t-1}$)	0.049988 (0.074)	0.057220 (0.027)
Constant	6.984484 (0.000)	6.550670 (0.000)

Thus, the financial growth of off-cluster firms' group was analysed using Equation 5.5:

$$ln(Turnover_{i,t}) = B_1 \times Emps_{i,t}^2 + B_2 \times Emps_{i,t} + B_3 \times Age_{i,t} + B_4 \times ln(R\,\&\,D_{i,t-1}) + U_i + C$$

Equation 5.5: Financial Growth Regression Model (Off-cluster)

The results show B_1 = -0.001799, B_2 = 0 .271634, B_3= -0.0463063, B_4= 0.0977126 where Emps is the number of employees for firm (*i*) in year (*t*), Age is the firm age (*i*), in year (*t*), and $ln(R\&D_{i,t-1})$ is the growth rate in R&D for firm (*i*) in the previous year (*t-1*), with fixed effect and no time fixed effect. The results show a complex (quadratic) relationship between the number of employees (this is similar to the results obtained for on-cluster firms), but also the negative linear relationship between firms age and financial growth indicates that the older the firm gets, the less it will grow financially. As in the case with on-cluster firms, the growth in R&D in the previous year resulted in positive growth in financial performance.

5.4.3 Firms innovation

The ratio of the value of patents to turnover was used as a “score” to measure the innovation, and this was detailed further into innovation input (the costs of networking and R&D), and innovation outputs (income from patented products and processes as well as licencing of patents). Innovation output has already been described (Equation 5.2). For innovation input, we used the following (Equation 5.6 and Equation 5.7):

$$SES_{i,t} = \frac{SE_{i,t}}{Turnover_{i,t}}$$

Equation 5.6: Socialising Score

Where *SES* is the social expenses score in the year (*t*), and *SE* is the actual value of the social expenses.

$$R\,\&\,DS_{i,t} = \frac{R\,\&\,D_{i,t}}{Turnover_{i,t}}$$

Equation 5.7: R&D Score

Where *R&DS* is the R&D investment score for the firm (*i*) in the year (*t*); however, no relationship was found between R&D score and *Innov* score.

Table 5.15 Innovation in on-cluster firms,
(Random VS Fixed Effects)

Parameter	Fixed Effect Coefficient (p-value)	Random Effect Coefficient (p-value)
B1 ($SES2_{i,t}$)	- 0.052944 (0.000)	- 0.050111 (0.000)
B2 ($SES_{i,t}$)	3.693099 (0.000)	3.603987 (0.000)
Constant	- 0.568068 (0.000)	- 0.566238 (0.000)

After checking regressions, Equation 5.8 was used to measure innovation impact.

$$Innov_{i,t} = B_1 \times SES_{i,t}^{\ 2} + B_2 \times SES_{i,t} + U_i + C$$

Equation 5.8: Innovation Regression Model (On-Cluster)

Where *SES* is the social expenses score for the firm (*i*), in the year (*t*). The test resulted (R^2 = 78%), which indicates a model with a good fit, and the Hausman test reports (Prob>chi^2 = 0.0000), rejected the null hypothesis, and concluded that fixed effect model is the most appropriate model. Checking for presence of time fixed effect produced a p-value of (0.9198) suggesting that time fixed effect is not essential.

It was then checked if the same model works for the off-cluster group, applying both fixed and random effect models. Table 5.16 shows that for off-cluster firms, the test resulted in a bad fit due to weak parameter p-values (table 5.16).

Table 5.16 Off-Cluster Firms Innovation Capabilities Model for off-cluster firms (applying equation 5.6).

Parameter	Fixed Effect Coefficient(p-value)	Random Effect Coefficient(p-value)
B1 ($SES2_{i,t}$)	-1.38 × 10-6 (0.978)	2.78 × 10-6 (0.954)
B2 ($SES_{i,t}$)	0.000164 (0.978)	- 0.000332 (0.953)
Constant	0.00521 (0.005)	0.011828 (0.156)

Models were then checked for any sign of correlations between innovation (Innov) and (a) investment made by shareholders or groups, (b) firms' maturity (measured as age), and (c) the size of the firms. However, none of these factors produced any statistically significant p-values. Thus, the model resulted in Equation 5.9:

$$Innov_{i,t} = B_1 \times R\,\&\,D_{i,t} + B_2 \times SC_{i,t} + U_i + C$$

Equation 5.9: Innovation Regression Model (Off-Cluster)

Where B_1= -4.17 $\times 10^{-6}$, B_2=-2.18 $\times 10^{-6}$, *SC* is the shareholders' contributions, and *R&D* is the R&D investment for the firm (*i*), in the year (*t*) with random effect as proved by Hausman test. Both parameters show a negative correlation with innovation capabilities. However, the coefficient is very small (closed to zero) meaning that their impact is most likely random, and there are no significant factors influencing innovation in off-cluster firms.

5.4.4 Results and analysis

5.4.4.1 Firms employment growth

Confirming earlier results (Davila et al., 2003; Grilli and Murtinu, 2014), the results presented here show that receiving investments through shareholders will positively impact the firms' employment growth. Firms that are on-cluster are expected to innovate in order to grow. Thus, investments and innovations are positively related to growth in employment growth.

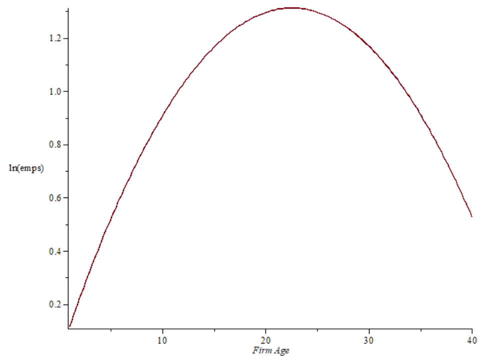

Figure 5.4 On-cluster Firms Age VS Employment Growth: Pertaining to on-cluster firms; age VS financial growth as based on ($B_1 \times Age^2_{i,t} + B_2 \times Age_{i,t}$) part of Equation 5.1 showing the quadratic relationship between the age and employment growth for on-cluster firms.

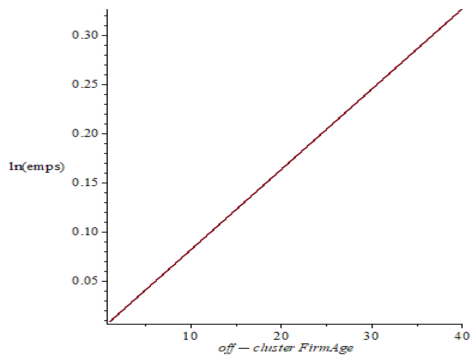

Figure 5.5 Off-cluster Firms' Age VS Employment Growth: Pertaining to off-cluster firms; age VS financial growth as based on ($B_1 \times Age_{i,t}$) part of Equation 5.3, which shows the nature of the linear relationship between age and firms' employment growth for the off-cluster firms.

The age of a firm has a more complex relationship with employment growth ln(emps) and Figure 5.4 presents the quadratic function obtained from using the values B1, and B2 showing that employment in a firm will grow until a certain age, whereupon it starts to slow down. These results are consistent with those reported by (Diez-Vial and Fernández-Olmos, 2017), who found that young firms benefit most from being located in clusters, but that these benefits become less when firms mature. Other interpretations are also possible, for example, that while on-cluster firms mature and plateaux-out, those that are more successful leave the cluster. However, for the case of off-cluster, the relationship between firms' age and growth is more linear, which might indicate that across the age off-cluster firms will perform better, but that is not the case if we compare the age to its corresponding value of ln(emps). For example, comparing the outcome for firms at age 20 for off- and on-cluster shows that ln(emps) = 0.17 for the off-cluster group, while it is around 1.1 for the on-cluster group. This indicates that on-cluster firms are growing faster (using ln(emps)) although off-cluster firms are growing linearly throughout their life cycle.

The growth of off-clusters firms is mainly dominated by investments coming from shareholders investment, which increases upon firm maturity, while innovation has a negligible impact on employment. This may be explained by the nature of firms located off-cluster, which are dominated by micro-firms (75%), possibly contractors or involved in similar support functions. Similarly, the impact of shareholder contributions

in on-cluster firms is a lot larger than for off-cluster. Other factors influencing the growth of off-cluster firms' growth is the score of the social expense, which is negatively influencing employment development, which is not the case of on-cluster firms.

Moreover, at the aggregate level, 5.3.1 findings highlighted the importance of cluster age, where the relationship between cluster age and number of employees follows a logarithmic function, where the number of employees is increasing up until certain cluster age, then it stabilises. Both results complement each other, when cluster becomes older, most likely its firms become older, and since firms' employment slows down or slowly decline, this will result in slow overall cluster development.

In conclusion, firms inside a cluster need to be more innovation-focused in order to grow, and they have to pay more attention to the maturity of the firm as well as the cluster. Next, we will discuss the factors that influence financial growth, which is the other aspect of firms' growth.

5.4.4.2 Firms financial growth

The data in Table 5.13 indicates that when an on-cluster firm innovates, then despite a financial penalty, increased financial growth is probable in the subsequent year. In particular, the relationship with *R&D* growth ($ln(R\&D_{i,t-1})$) also shows that if a firm R&D investment has grown in the previous year, then the result is higher turnover (income), in the next year(s). This agrees with interpretations of, e.g. investing in a patent one year and reaping the benefit in subsequent years, as is the case for employment growth (previous section). However, as shown in figure 5.6, the relationship between the maturity of firms and financial growth is quadratic and more complex.

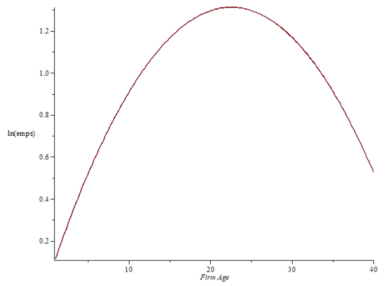

Figure 5.6 On-cluster Firms Age VS Financial Growth: Pertaining to on-cluster firms; age VS financial growth as based on ($B_3 \times Age_{i,t}^2 + B_4 \times Age$) part of Equation 5.4, which presents the quadratic relationship between on-cluster firm age and financial growth.

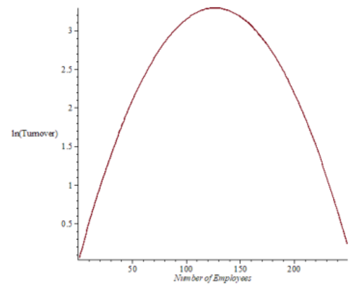

Figure 5.7 On-cluster Firms' Sizes VS Financial Growth: Pertaining to on-cluster firms; age VS financial growth as based on $(B_1 \times Emp_{i,t}^2 + B_2 \times Emp_{i,t})$ part of Equation 5.4 showing the quadratic relationship between on-cluster firm size and financial growth.

Figure 5.6 shows that when firms get older, financial growth slows down. This may be artefactual or, put simply, it is easier to double the turnover of a firm with 1 million per year than to double the turnover of a firm with 100 million per year. Nonetheless, the data can be compared with turnover and Figure 5.6 and Figure 5.7 show that size and maturity of firms show an optimal age and size of on-cluster firms: Figure 5.6 and figure 5.7 combined show that on-cluster firms grow from age zero into around seventeen years old and from size one employee to around hundred and thirty employees. One hypothesis could be that at this stage, owners either decide on a strategy of ‘capped growth’ (Mellor, 2011; Mellor, 2014a) staying within the cluster or decide on a riskier high-growth strategy outside the cluster.

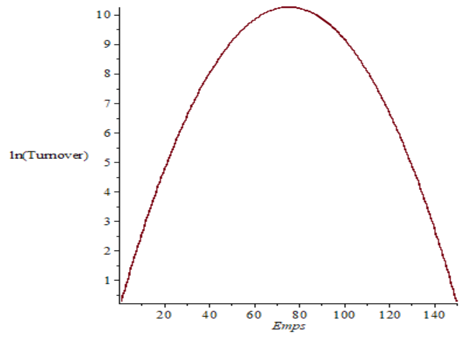

Figure 5.8 Off-cluster Number of Employees VS ln(turnover) extracted by applying partial: Pertaining to off-cluster firms: Number of employees VS ln(turnover) as extracted by applying partial of Equation 5.5.

In the difference between on- and off-cluster firms, the firm's size has a similar relationship as in the case of on-cluster firms (a quadratic relationship). However, when plotting this relationship (figure 5.8), it shows that the optimal size is a lot less than the one for the on-cluster firms' group (around 70 employees VS 130). This indicates that being on-cluster would result in a better growth curve relative to the firm size. Again, these plots do not take other factors into account (only firm size). Moreover, there is a statistically significant relationship between the growth in R&D and financial growth (when using the panel model with random effect), which is similar between the two groups except for that firm age (maturity) negatively impacts turnover growth for off-cluster firms. However, for off-cluster firms, the production of innovations is not relevant to performance, which again could indicate that off-cluster firms may contain significant numbers of contractors.

Moreover, section 5.3.3 found that the overall cluster financial return is mainly influenced by the cluster size, while at the micro-level, it is affected by multiple factors. Therefore, both results complement each other. Meaning that, while the cluster manager must consider increasing the size of the cluster, firms' manager must look into producing more innovation, which at the end helps both to achieve the highest financial growth. In conclusion, it is obvious that firms (on- and off-cluster) are affected by size and age, but the on-cluster firms are more distinguished by their innovation capabilities.

5.4.4.3 Firms innovation

Al-kfairy et al. (2018) showed that on-cluster firms produced a significantly higher innovation output than off-cluster ones, and on-cluster innovation investment produced higher outputs than it did for off-cluster firms. Moreover, at a group level, on-cluster firms maintain better financial performance. This is supported by the data in Table 5.15 and Table 5.16, which show a lack of correlation due to poor p-values, indicating that innovation in on- and off-cluster firms have different dependencies. However, no relationship was found between *R&DS* score and *Innov* score. This could indicate that for on-cluster firms, innovation score depends on networking (socialising). To test this, the relationship between SES and Innov was plotted. Figure 27 shows the simulated SES scores from 1% to 80% against innovation. Figure 5.9 shows that it is networking is the most important factor to achieve a higher innovation score.

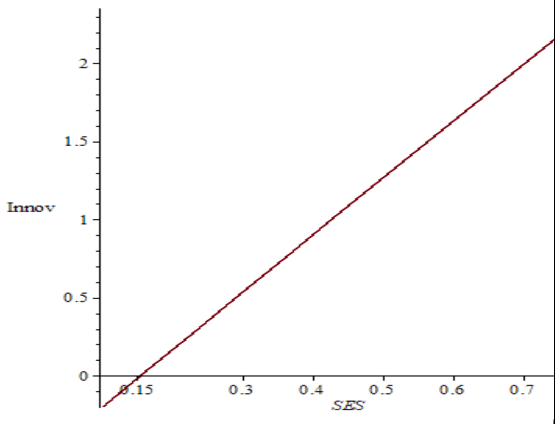

Figure 5.9 Showing the effect of SES against Innovation Capabilities for on-cluster firms (minus innovation score values are just for illustration).

Furthermore, figure 5.9 shows that in order to innovate, on-cluster firms have to spend more than 15% of turnover on organising social events, networking, partnership with other firms, etc. Although, some networking activities (informal) channels would be without direct overheads, e.g. lunchtime meetings, or personal friendship. Moreover, it shows that expenditure on social activities brings rewards in terms of innovation. Moreover, as the results derived from Equation 5.2 and Equation 5.1 shows, there are a positive relationship between on-cluster firms innovation and both employment and financial growth, which in turn indicates that growth of on-cluster firms is mainly dependent on innovation capabilities. This supports earlier results showing that for single organisations, innovations accrued through networks are almost as valuable as “homegrown” innovations (Mellor, 2015). Off-cluster firms show negligible effects of R&D, and shareholders investments and no correlation were seen between off-cluster firms’ innovation and employment or financial growth.

Furthermore, previous sections 5.3.2 for the aggregate-level cluster innovation confirms the results obtained for the micro-level innovation, where both are dependent on networking (measured as social expenses). In conclusion, networking in any form (formal or informal) would normally result in more innovation. This fact is confirmed for on-cluster firms,

5.4.5 Discussion

Table 5.17 distinguishes between different factors that influence both on- and off-cluster firms, which proves that on-cluster success factors are more consistent than the off-cluster ones. For example, shareholders contribution impact is always positive on employment growth for on-cluster firms, which makes it much easier to decide the needed policy (more investment), on the other hand, it reports a contradicting result in case of off-cluster firms, which (in turn) makes it harder to decide the appropriate policy. Similar results were obtained for firms' ages. From these results, we can conclude that factor influencing on-cluster firms' development are more deterministic, while for the off-cluster firms are not, and more as random impact.

The results are summarised in figure 5.10, illustrating that innovation capability is a major determinant for both financial and employment growth. On-cluster, however, innovation capacity is mainly influenced by networking (measured as social expenditures). This highlights the importance of networking for on-cluster firms, which implies that firm managers, as well as cluster managers, should facilitate social events and networking activities both between and within companies. These findings are consistent with earlier results, where for example, Al-kfairy et al. (2017) found that networking is the main determinant of innovation capabilities for business clusters at the aggregate level, while others support these findings at the micro-level (Bell, 2005, Squicciarini, 2008; Dettwiler et al., 2006).

Table 5.17 Summary of Success Factors Findings

Factor examined	On cluster	Off cluster
Shareholders' investment	Positive linear (affecting employment growth)	Positive linear (affecting employment growth), negative linear for innovation capabilities.
Firms' age	Quadratic (affecting employment growth), quadratic (effecting financial growth)	Positive linear (effecting firms' employment growth), negative linear (effecting financial growth).
Firms' sizes	Quadratic (effecting financial growth)	Quadratic (effecting financial growth)
Innovation capabilities	Positive linear (affecting employment and financial growth)	NA
Social Expenses Score (SES)	Positive linear (effecting innovation capabilities)	Negative linear (effecting firms employment growth), negative linear (effecting innovation capabilities)
ln(R&D)	Positive linear (effecting financial growth)	Positive linear (effecting financial growth).
R&D	NA	Negative linear (effecting innovation capabilities)

It shows the contradicting impact of off-cluster firms success factors, while on-cluster success factors are more stable (the sign of the impact does not change).

NA = Not Applicable (no impact)

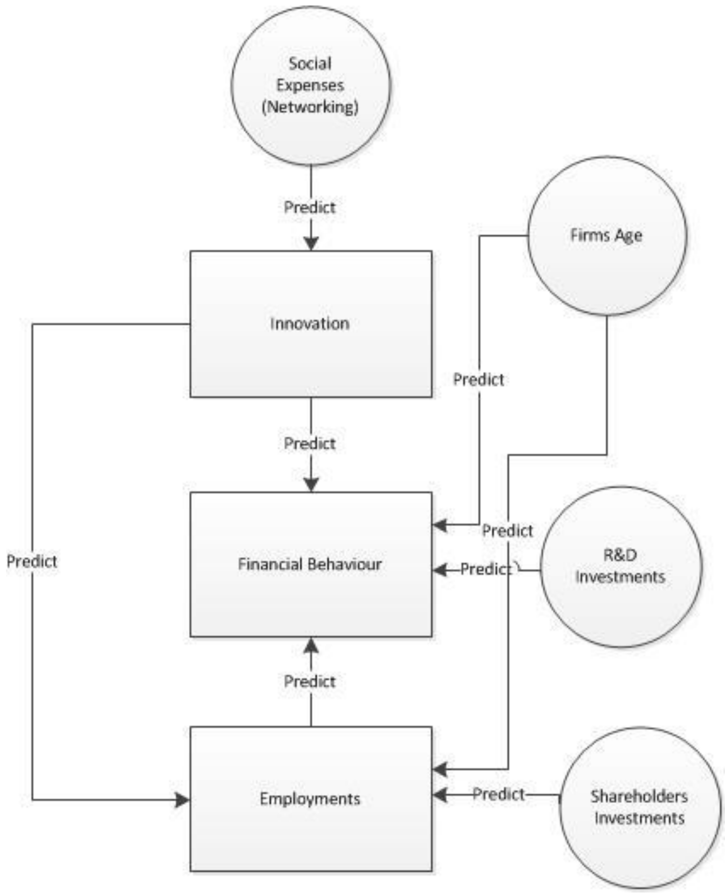

Figure 5.10 On-Cluster Firms' Success Factors Summary

Age is also an important factor for policymakers due to considerations around local employment (Diez-Vial and Fernández-Olmos, 2017). The results presented here show that growth, independently of how this is measured, proceeds apace up to age ~17, after that growth in turnover starts to decline. Thus, our initial hypothesis is that firms grow on-cluster and innovate by networking, then either stay and plateau-out or, if they have achieved successful innovations, they "graduate" and move away from the cluster (and perhaps away from the region). Unfortunately, this hypothesis cannot be investigated with the data at hand, and further analysis must be done.

Factors such as R&D investments and shareholders contribution highlights the importance of having on-cluster firms supported by investment bodies because these lead to increasing both employment and financial growth. This supports the triple helix view of business clusters connecting public, venture capitals and higher education institutions (Klofsten et al., 1999; Etzkowitz and Leydesdorff, 2000; Kim et al., 2014). Moreover, it is consistent with the results of (Al-kfairy et al., 2019b) who showed that especially during the early stages of a cluster, the most efficient topology for an STP is a central initiative surrounded by a star structure of companies.

5.5 Conclusion

This chapter focused on findings factors influence firms' performance at both aggregate and micro-level by exploring different models (see appendix 1 for a sample of models we tried). The aggregate level analyses of different growth matrixes, considering cluster firms as one entity. The next part discussed factors impact development at firms' level.

Results show a very consistent relationship between cluster as one entity and its firms. The main determinant for overall cluster development is cluster age, size, and networking. Figure 5.11 summarises the findings at aggregate-level. It shows that cluster age is the most important factor, which highlights the importance of monitoring the ageing impact on cluster. It underlines the importance of both size and socialising (networking) on sustaining cluster development. Figure 5.11 act more as an evaluation platform for cluster development, which includes a number of steps for policymakers to evaluate if a cluster is behaving as expected or not. If not, it can help in to produce the right policy. For example, if it is identified that cluster financial situation is not good due to very few firms entering into it, then policymakers would need to encourage incubation programmes or attract MNC to move into the cluster. Moreover, if a cluster is believed to produce fewer innovations, which will impact the overall system, then policymakers may need to evaluate if there are enough networking events and partnership agreements occur in the cluster and this should be harmonised with cluster size.

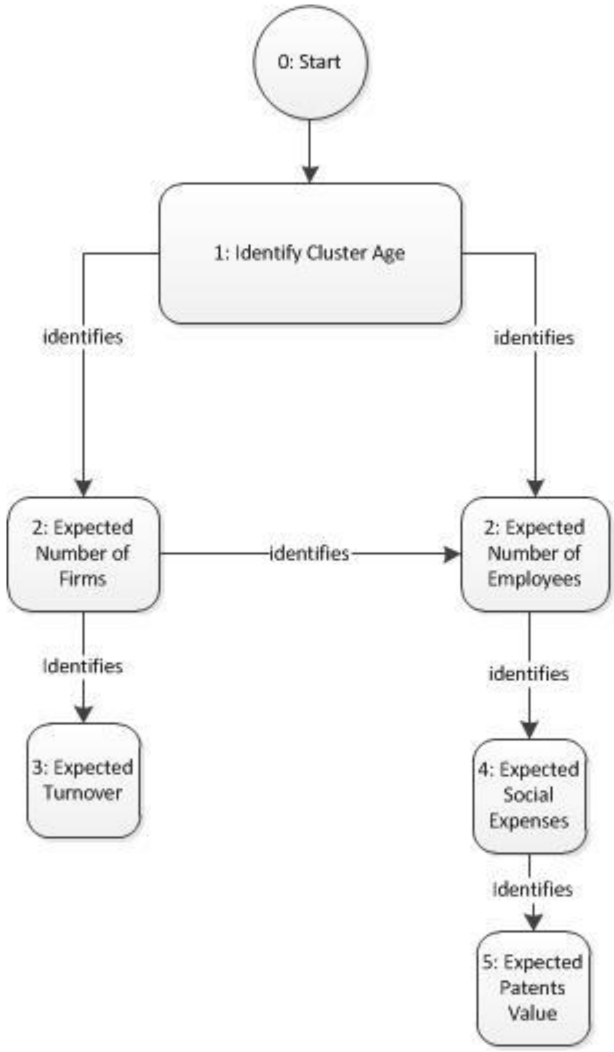

Figure 5.11 Summary of Aggregate Level Prediction Models

On the other hand, figure 5.10 summarises the findings for micro-level analysis, which connects all the models to obtain a fair picture of what are the most important factors influencing firms' success inside business clusters. The figure shows which factor can be used to predict other factors, which leads us to rank these factors.

It is clear that firms' age is a very important factor since it influences both the financial and employment growth of firms. This implies that cluster and company managers should carefully consider the right firms' exit age from the business cluster (assuming that firms are born inside the cluster). However, as firm age is non-linearly correlated with both factors, then it is possible to predict the optimal firm's ages to achieve the best financial and employment growth, but we need to control for other indicators. Moreover, innovation (measured as patents value ratio to turnover) is another important indicator with the same number of arrows as firms age. This indicates that business clusters' firms can be distinguished by their innovation capabilities, which is positively correlated with both financial and employment growth. However, as innovation on-cluster depends on the amount of networking (measured as socialising expenditure), this indicates that socialising is another very important indicator characterising business cluster firms.

Less important factors (by the number of arrows) include shareholders' investment, which is a positive indicator of employment growth. Meaning that if a firm receives a shareholders' contribution, then they will normally use that money for employing new people. However, group contribution does not have any impact on employment growth. This indicates that being part of a group does not necessarily mean they can grow faster than any other firms (in size or financially). Moreover, previous year growth in R&D implies positive financial growth in the next year. This may indicate that firms' investment in R&D may help firms to financially grow more. In other words, investing in R&D means that things are happening inside firms, which is not related to patents innovation (as we could not find a correlation between R&D and patents value), but these things result in a better financial performance. Furthermore, this confirms that R&D impact on financial performance is not current, and rather it is an investment for the future.

These results are inconsistent with previously obtained results at the aggregate level, where the cluster age is considered as one of the most important factors influencing cluster development at the aggregate level, similarly is the firms' age at the micro-level. Moreover, at the aggregate level, cluster size was found as the second most important factor presented by the number of firms and employees, at the firms' level we found that innovation is the second important factor. However, firms' size was one important factor influencing it is financial growth, which is similar to the aggregate level analysis findings. Furthermore, networking (social expenses) is an important factor for both firms' and cluster as they influence the innovation output. On the other hand, our analysis found that R&D investment influences innovation output for off-cluster firms' group, which indicates that networking for an on-cluster inhabitant is more beneficial than for off-cluster firms. In conclusion, we believe that these findings will help policymakers in identifying the needed policies when evaluating business cluster and firms' performance. Given the importance of networking, the next chapter discusses how cluster organisation structure impacts innovation distribution through knowledge spillover to obtain a clearer picture of connecting all success factors.

Chapter 6: Simulation of Business clusters Optimal Structure (topology)

6.1 Introduction

Business clusters are tools for fostering innovation between the firms inhabiting the cluster. Networking channels are considered as integral parts of the knowledge exchange process, and therefore, the innovation process. Previous chapters show the importance of socialising and networking in knowledge spillover process as well as enhancing cluster innovation capabilities, where the most important factor influencing cluster innovation capabilities is social expenses at both aggregates as well as micro-level. This highlights the importance of analysing how innovation is distributed between the different cluster structure topologies, which is aligned with previous studies.

Thus, this chapter simulated three networking topologies for business clusters; the star model, where all are connected to central organization, called a cluster initiative (CI), the strongly connected model, when all are connected to each other, and finally the randomly connected model, when the firms' network does not follow any centralized topology. These models assume that the transaction costs for communication between gatekeepers is the major variable and for simplicity, we exclude background costs like lease and utilities because these are constant, as well as there is no risk-sharing between on-cluster firms and that specialised relationships (e.g. supply chain) do not occur.

Selection of –topologies was based on the earlier study of (Markusen, 1996) who distinguished between four different types of general business clusters:

1. "Marshallian industrial districts" which shapes a randomly connected network.

2. “Hub-and-spoke” district, where knowledge spillover occurs through different cluster hubs or central organisation, which is considered to be the main source of coordination.
3. “Satellite industrial district”; which is a critical mass but can be quite difficult to consider as a cluster.
4. “State-centred” industrial districts, when STPs are built around one or more government-controlled research institutions or state-supported cluster-coordinating organisations (the cluster initiative or CI) is established.

Above topologies can be mapped as the following networking topologies, ‘Marshallian industrial districts’ would be a randomly connected model, while ‘hub-and-spoke’ district model and “state-centred” would be considered as star topological structure, and strongly connected model for a strongly connected ‘hub-and-spoke’.

Topologies were analysed using adjacency matrixes, and Monte-Carlo simulation (cellular automata), trading transaction (networking) costs against knowledge benefit. Results show that star topology is the most efficient form from the cost perspective, and this is especially the case for business clusters in the early stages of their development. However, when the cost of knowledge transformation is lowered, then the strongly connected model is the most efficient topology, followed by the randomly connected model.

This chapter starts by discussing the foundations behind the simulation approach used, then results of the simulation are discussed in 6.3, after that the results for different topologies are compared, and concludes the findings of the section. This chapter is built using the author’s contribution in (Al-kfairy et al., 2019b)

6.2 Methodology

In this study, we modelled three different scenarios of tech-hub network topology, which are:

1. Star model, where all enterprises are connected to one central organisation, the Cluster Initiative (CI). CI is defined as a central intermediary organisation, which is trying to help business clusters to grow [see (Klofsten et al., 2015)], by, e.g. connecting firms with VC (Venture Capital) and public bodies. In the model, each constituent organisation has exactly one tie connected to the central organisation, and all clusters' firms are connected through that organisation, in this case, CI represents the cluster 'hub', and all firms are connected to it (state cantered cluster). Typically, this is the case for the development of science parks like Mjärdevi Science Park in Sweden (Hommen et al., 2006; Mjardevi Science Park, 2016). Moreover, it is a crucial part of the triple helix phenomena, which connects public, private and higher education institutions (Etzkowitz and Leydesdorff, 2000). Figure 6.1 illustrates this model (All connections are bi-directional with the same effect).

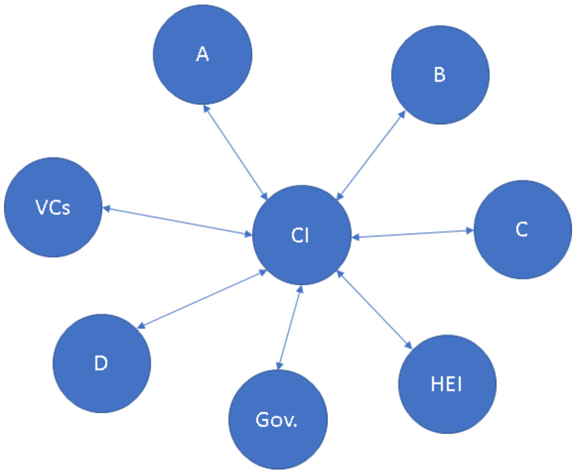

Figure 6.1 Business Cluster Star topology, where CI=Cluster Initiative, VCs =Venture Capital and Gov =Government and HEI=Higher Education Institution

2. Strongly connected model. This model represents the case when all companies are centric and connected to each other. For example, if we have (*N*) companies, then each company is connected to (*N-1*) companies. In this case, all firms are centric to the network, and knowledge sharing takes place between all firms simultaneously. This represents a strong "spoke-and-hub" topology (Figure 6.2).

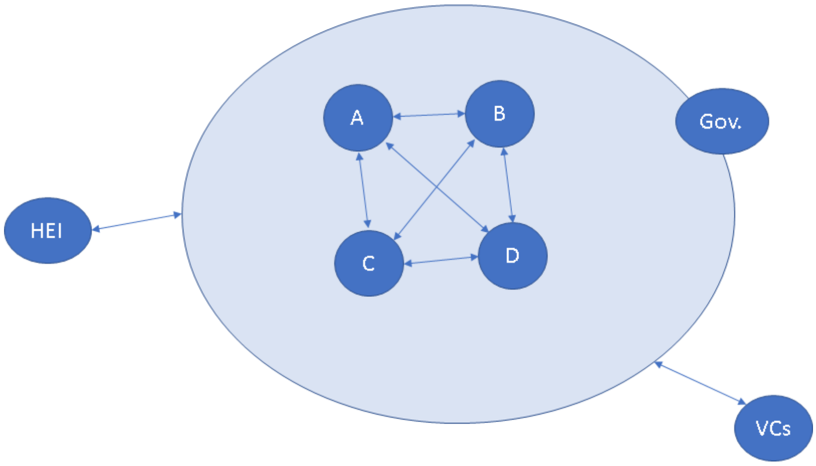

Figure 6.2 Business Cluster Strongly Connected Model, where Gov=Government, VCs =Venture Capital and HEI=Higher Education Institution.

3. Tree model (Multi-Level) of randomly connected firms. This represents randomly connected firms within the cluster; when firms are connected to a subset of firms in first level direct connection (L_1), another subset of level two (L_2), level three (L_3) and some firms are still isolated. Where L_1, L_2, L_3 and L_D represent the number of firms connected in level one, two, three and 1,2,3 and D represent the distance between the firms. This cluster topology represents different structures (mainly Marshallian districts), where there are multiple "cluster hubs" with accompanying firms surrounding them (Figure 6.3).

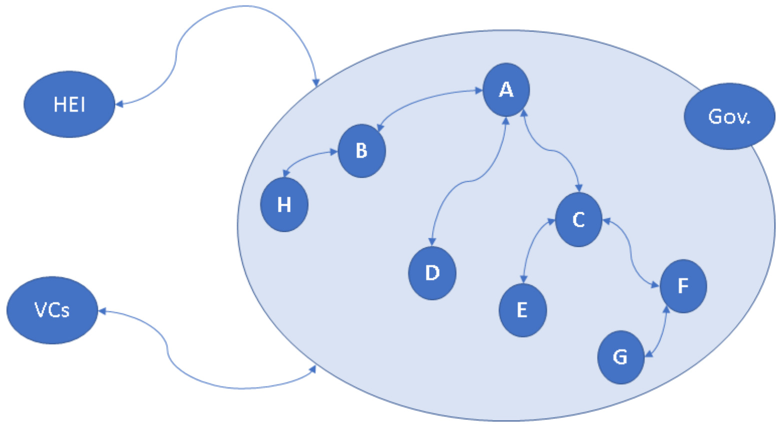

Figure 6.3 Business Cluster Randomly Connected Model

In all three models, each connection is apportioned a networking cost that is attached to communication between information gatekeepers, as well as within the firm. This cost is a net sum of time spent building trust, adaptation, re-design or discussion time. This represents the cost (c) drawn randomly from a normal distribution with a random mean (μ, selected to be $0 \leq \mu \leq 100$) where the cost was included for cases when the costs for communication tend to zero, e.g. lunchtime meetings or personal friendship events, and here $\sigma 2$ is equated to 1. In this scenario, each company will gain some benefits (b) from the knowledge obtained. Assuming that the value of the knowledge gained will always be positive, then the benefits (b) will be randomly obtained with ($1 \leq \mu \leq 100$) and σ^2 will be unity (1).

Because IASP reported that the current STP contains between less than 50 firms and somewhat over 1000 firms, and where most STPs host between (100 – 400) firms, we initiated a computer model where the average number of firms was randomly obtained between 6 and 500 firms, i.e. well within the outliers. Then the firms put into a topological shortest path (NxN) matrix of firms (F), which was generated from an adjacency matrix. Three symmetric (NxN) matrices were generated:

1. Cost Matrix (C), which includes the costs of random ties between firms, because the connection is assumed to be bi-directional, meaning that we count only one symmetrical connection between two firms.

2. Benefit Matrix (B), this includes random ties gains and the same C and B were used for all three topologies examined to ensure case-by-case consistency.

3. Distance Matrix (D) refers to the third topology and consists of the assumed distance between randomly connected firms.

Next, Monte Carlo simulations were performed with 1000 iterations but with differing average numbers of employees, the number of firms, average time and firms' matrices, according to the topology selected. The results were initially stored in Microsoft Excel files and subsequently injected into SPSS for further analysis.

6.3 Simulation results

6.3.1 Star topology

In the star model, as presented in Figure 6.1, each firm (N_i) is connected to a central node, called the CI (cluster initiative). The cluster initiative (CI) is responsible for coordination between the firm-level information gatekeepers, and therefore each firm possesses only one connection (to the CI), and the information gatekeeper will share obtained knowledge openly with their firm. If the CI is represented by the firm at index (*1*), then the net benefit of networking for firm *j* will be $B_{1,j} - C_{1,j}$, *where* $j \neq 1$. Put simply, we go through the first row of the cost and benefit matrices.

$$\pi = \sum_{j=2}^{N} B_{1,j} - C_{1,j}$$

Equation 6.1: Star Topology Net Innovation Benefit

From the adjacency matrix, a distance matrix was generated (table 6.1), where the distance between each firm and the central organisation (A) is 1, and between each firm and other firms is precisely 2. Communication is always happening through the central organisation, which obviates the need to incur the costs of walking the whole path between two different firms.

Table 6.1 Star Model Adjacency Matrix

Firms	A	B	C	D
A	0	1	1	1
B	1	0	2	2
C	1	2	0	2
D	1	2	2	0

Using the configuration described above, figure 6.4 shows that in the extreme worst case, the total gross benefit can be up to -31677. Conversely, the extreme best case would be 40668 with a mean of -390. The Pearson correlation between average benefits, average cost, and average number of firms with gross benefit show that the average number of firms has no effect on the total gross gain (correlation coefficient = -0.063 and p-value = 0.045), while the average cost is the main determinant of the gross benefit (correlation coefficient = -0.613 and p-value less than 0.001), with less effect from average gain (correlation coefficient = 0.599 and p-value less than 0.001). These results imply that, even though this topology can minimise the damage, it does not maximise the benefit. In other words, this topology is beneficial under those conditions where the investment involved in networking is high, regardless of the cluster size.

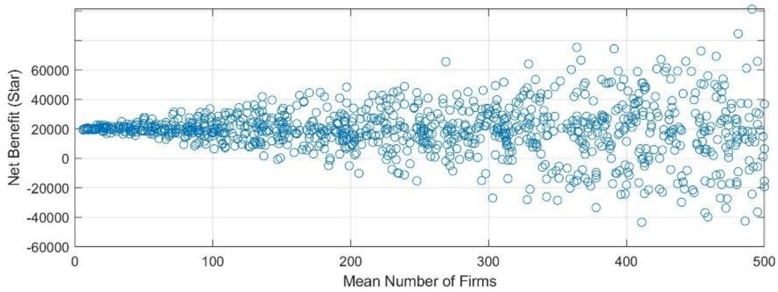

Figure 6.4 Star Model: Mean Number of Firms to Net Benefit

6.3.2 Strongly connected topology

In this model, all firms in the business cluster are in a centric position and cross-linked. The transaction costs incurred between firms are obtained from the matrix C, where each index represent the connection between firm (i) and firm (j), then the matrix entry $C_{i,j}$ and equivalent are the benefits from the connection Bi,j. However, the connection is bi-directional meaning it counts for (i) and (j) connection as well as j and i. Therefore, the connection i,j is only counted and the connection j, and i neglected, so that we go through half of each matrix (C, and B) instead of the whole matrix. This is also true for the third topology (randomly connected). Similar to a star topology, the distance factor for this topology was ignored. To sum, the total net benefit can be obtained by applying equation 6.2 (connection benefit minus connection cost):

$$\pi = \sum_{i=1,\, j=1}^{N} B_{i,j} - C_{i,j} \text{ , where } i \neq j$$

Equation 6.2: Strongly Connected Topology Net Benefit

Table 6.2 Strongly Connected Model

Adjacency Matrix

Firms	A	B	C	D
A	0	1	1	1
B	1	0	1	1
C	1	1	0	1
D	1	1	1	0

Figures 6.5 and 6.6 present two scatter plots regarding the number of firms (*N*), net benefit (π) as well as mean cost, respectively. A sample of the simulation output is shown in Table 6.3. Descriptive statistics regarding minimum, maximum, and average net benefit are shown in

Table 6.4. The analysis of the data shows that the strongly connected topology can be much more beneficial for the STP and the client firms involved than the star topology is. However, in the worst case, it can also be very harmful, for example in the case where only low benefits accrue accompanied by near-exponentially expanding co-operation costs, so if direct ties do not result in tangible benefits, then this scenario would be very expensive.

Table 6.3 Strongly Connected Topology Sample Simulation Output

Mean Number of Firms	Mean Benefit	Mean Cost	Strongly connected (Net Benefit)
409.00	12.79	57.54	-3,734,216.00
431.00	12.57	0.64	1,076,628.00
471.00	34.77	3.26	3,487,064.00
306.00	13.24	2.84	485,089.50
17.00	33.90	26.30	1,014.37
389.00	12.69	26.48	-1,041,321.00
225.00	23.74	3.72	504,552.00
283.00	7.03	3.34	146,831.40
493.00	6.72	15.74	-1,093,278.00
339.00	6.55	45.05	-2,205,142.00
34.00	76.96	2.91	41,501.31

Table 6.4 Strongly Connected Model Descriptive Statistics

	Minimum Net Benefit	Maximum Net Benefit	Mean Net Benefit	Standard deviation (Net benefit)
Strongly connected	-7,611,257.90	9,976,724.80	-86,316.50	1,620,837.90

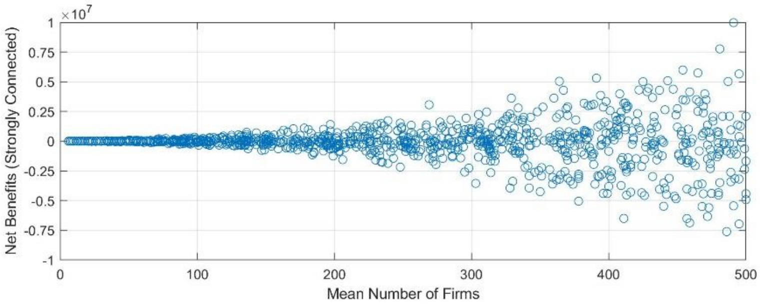

Figure 6.5 Strongly Connect Model: Mean Number of Firms to Net Benefit

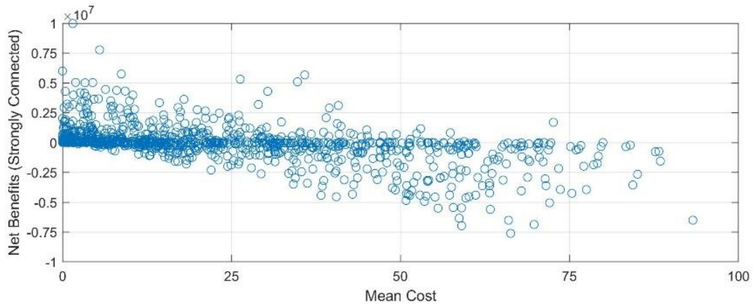

Figure 6.6 Strongly Connected Model: Mean Cost to Net Benefit

Moreover, correlation analysis shows that cluster size (number of firms) has no impact on the gross benefit (same conclusion as for the star topology), while both mean cost and mean benefit has almost-equivalent impact (one positive for mean benefit, and one negative for mean cost) with (correlation coefficient = 0.504 and -0.520, with p-value of less than 0.001 for both of them). One observation is that the impact of cost for strongly connected, is less than the star topology, while the impact of mean benefit is similar.

6.3.3 Multi-level (tree) topology

In reality, clusters will not follow a specific networking topology, especially when the agglomeration will tend to follow demand rather than a stricter state vision. Thus, firms will eventually become connected to firms that interest them in a mixed topology. For example, firm (X) could establish a partnership agreement with another firm (Y), a supplier for example, which would establish another partnership with another supplier (Z), this would create the pairs (X, Y) and (Y, Z) which indicates that firm (X) is connected to the firm (Z) through firm (Y), and indeed this chain can be much longer, but for simplicity in this model we assume that it is a maximum of four levels. In this case, there will be firms which are more centric than other firms, and some firms which are more isolated and therefore need to build connection networks. Consequently, a distance factor must be added to the total cost. For simplicity, we assume that the distance will be multiplied by the cost, so if the distance becomes two, then the cost will be doubled, given that the first order distance is always one. Table 6.5 illustrates a sample distance matrix (D), in the asymmetric matrix, where the same distance is assumed between firm (i) and (j) as well as between (j) and (i). Similarly, to the strongly connected model, the connection cost and benefit were only counted once (half of the matrix).

Table 6.5: Multi-level Model Adjacency Matrix

Firms	A	B	C	D
A	0	2	1	2
B	2	0	1	2
C	1	1	0	1
D	2	2	3	0

$$\pi = \sum_{i=1, j=1}^{N} B_{i,j} - C_{i,j} \times D_{i,j} \text{ , where } i \neq j$$

Equation 6.3: Randomly Connected Model Net Benefit

Figures 6.7 and 6.8 show mean cost and mean gross benefit plotted against net benefit and the analysis indicates that there no correlation between net benefit and distance, with correlation coefficient -0.02, p-value = 0.534 implying that distance does not significantly affect final benefit. On the other hand, and in contrast to previous topologies, the number of firms exhibited a moderate impact on the net benefit of -0.432 with a p-value less than 0.001. Moreover, the mean gross benefit had a low impact on the final net benefit, while mean cost has a higher impact in this case than in the cases of the strongly connected and star models (-0.618 and p-value less than 0.001). This confirms that this topology can be helpful under conditions of low communication costs and high knowledge benefits, e.g. in smaller highly-specialised STPs.

Table 6.6 Multi-Level Model Descriptive Statistics

	Minimum Net Benefit	Maximum Net Benefit	Mean Net Benefit
Randomly connected	-19,323,860.80	9,692,557.80	-1,662,454.30

Moving on to build a fair picture of the overall topology effect we can check the descriptive statistics (

Table 6.6), which shows that, in the best-case, tree topology can be beneficial for the cluster. However, when the knowledge obtained is expensive, or if it is not particularly beneficial, then it is better to avoid this type of structure.

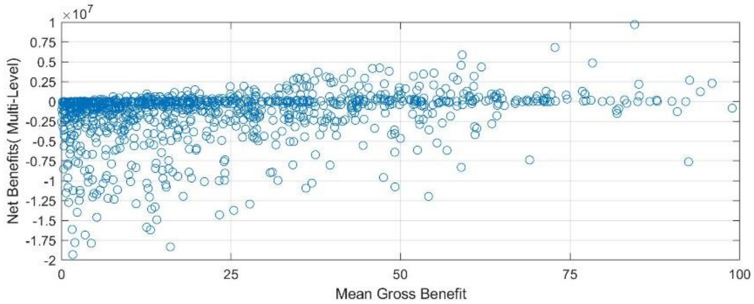

Figure 6.7 Multi-Level Model: Gross Benefit to Net Benefit

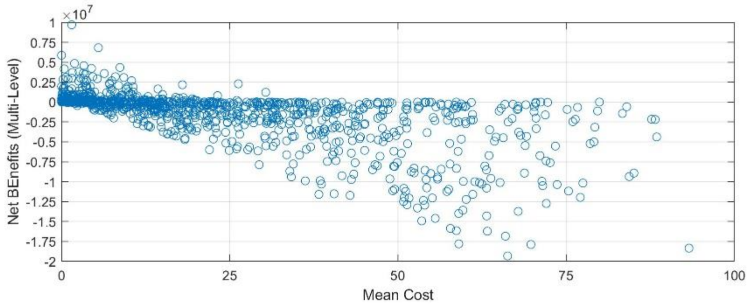

Figure 6.8 Multi-Level Model: Mean Cost to Net Benefit

6.4 Comparing topological structures

The previous sections presented the results obtained from simulating three different cluster topologies without a priori knowledge of which structure is better for an STP or why. In order to understand the effect of each structure on the development STPs, dummy variables were created, which are the size representing the STP size expressed as the number of firms and divided the STP into five groups (1 – 5), each group consists of 100 firms. Then divide the cost into four groups (1 - 4), resulting in 20 different categories, where the impact of the three different structures can be determined.

Table 6.7 - Table 6.9 presents the mean values of three different topologies with different sizes and cost categories. These tables confirm the findings presented in earlier sections that the main factor influencing the cluster net benefit from knowledge is the mean cost. These results, which focus on the mean values only show that the mean net gain upon implementing a strongly connected network structure (or even the randomly connected multi-level one) is better than the star model under conditions where the knowledge sharing cost is small, regardless of the cluster size. However, the star model becomes a better solution when the costs become more expensive.

We assume that during the early stages of an STP or when ideas/products are still young, the cost of sharing will be higher, especially if the firm's network is not well-established. Moreover, in case of state-centred STPs, most firms will be start-ups, SMEs etc and that inter-personal connections will hardly be matured, which in turn implies a costly development and knowledge sharing, which indicates that when STPs are still new, a star topology is the most efficient cluster topology.

However, when knowledge sharing costs are low, then as shown in tables 6.10 – 6.14, the strongly connected model will perform better. This means that as knowledge becomes more accessible and widespread (i.e. to be found in many firms) and the STP matures, then the cost of knowledge sharing and implementation will decrease, and as a consequence, the star model will not be as helpful as other models. Because the strongly connected model is the best performing model among all the three investigated, this implies that – at the firms' level – the more centric the firm is in the network, the more it will benefit from knowledge sharing.

The randomly (multi-level) topology is about as valuable as the strongly connected model, albeit that these benefits diminish as the cluster grows. Overall, the randomly connected topology is as efficient as the strongly connected topology under circumstances where the cost of knowledge sharing and application is low, i.e. the STP is still small, and the knowledge is mature. The drawback is that it is harder to transform this topology into a strongly connected topology if it becomes needed, and this may become a significant hurdle in future of that STPs development.

In conclusion, simulation results show that the star topology is the best, when the networking costs are high, which in turn is associated with the earlier stages of cluster development. On the other hand, later in STP development, when connection costs are low, a trust network is established, and knowledge benefits are high, then the strongly connected topology is most efficient. However, under these circumstances, the randomly connected model can also be as efficient as the strongly connected topology, albeit that this is affected by the STP size. In particular, tables

6.9, 6.10, and 6.11 shows that in multi-level only, when costs are smaller than benefits, does increase size tends to decrease the profit (net benefit). However, this is not the case for star and strongly connected models.

Table 6.7 Star Topology Net Benefits (Mean)

Size (Number of Firms) / Mean Cost	6-100 (Firms)	101-200 (Firms)	201-300 (Firms)	301-400 (Firms)	401-500 (Firms)
0.00 – 10.00	1,319.15	3,759.62	3,669.34	6,143.43	9,644.34
11.00 – 25.00	607.54	565.56	2,038.85	1,151.28	1,211.52
26.00 – 50.00	-662.81	-1,644.55	-4,014.13	-1,792.38	-4,730.21
51.00 – 100.00	-1,792.16	-6,062.40	-8,817.38	-15,780.70	-17,935.70

Table 6.8 Strongly Connected Topology Net Benefits (Mean)

Size (Number of Firms) / Mean Cost	6-100 (Firms)	101-200 (Firms)	201-300 (Firms)	301-400 (Firms)	401-500 (Firms)
0.00 – 10.00	44,725.65	285,229.80	463,710.90	1,086,392.00	2,162,513.00
11.00 – 25.00	21,533.38	40,932.74	256,963.20	186,220.40	241,816.80
26.00 – 50.00	-22,742.90	-129,100.00	-505,972.00	-308,025.00	-1,084,207.00
51.00 – 100.00	-66,553.60	-470,822.00	-1,088,210.00	-2,830,166.00	-4,037,838.00

Table 6.9 Multi-Level Topology Net Benefits (Mean)

Size (Number of Firms) / Mean Cost	6-100 (Firms)	101-200 (Firms)	201-300 (Firms)	301-400 (Firms)	401-500 (Firms)
0.00 – 10.00	35,019.43	207,093.10	262,121.60	690,955.90	1,490,524.59
11.00 – 25.00	-27,268.70	-253,275.00	-525,406.00	-1,413,441.00	-2,351,561.54
26.00 – 50.00	-117,532.00	-813,158.00	-2,283,365.00	-3,711,968.00	-6,583,097.32
51.00 –100.00	-255,283.00	-1,562,314.00	-3,839,448.00	-8,891,550.00	-12,936,421.06

Table 6.10 Mean Cost (0-10) and Mean Size (6-100 Firms)

Mean Size (6-100 Firms) Mean Cost (0 - 10)	Mean distance	Star (Net Benefit)	Strongly connected (Net Benefit)	Multi-Level (Net Benefit)
Mean	2.51	1,319.15	44,725.65	35,019.43
Median	3.00	703.22	14,124.11	10,078.32
STD	1.06	1,640.24	69,799.81	66,016.85
Max	4.00	6,821.34	334,663.20	304,809.60
Min	1.00	-589.71	-27,528.00	-90,011.10

Table 6.11 Mean Size(101 - 200 Firms), and Mean Cost(0-10)

Mean Size (101-200 Firms) Mean Cost (0 - 10)	Mean distance	Star (Net Benefit)	Strongly connected (Net Benefit)	Multi-Level (Net Benefit)
Mean	2.72	3,759.62	285,229.80	207,093.10
Median	3.00	2,499.64	183,646.20	117,001.10
STD	1.10	3,836.75	327,638.30	336,393.60
Max	4.00	14,220.06	1,400,465.00	1,276,355.00
Min	1.00	-759.35	-73,080.20	-360,072.00

Table 6.12 Mean Size (201 - 300 Firms) and Mean Cost (0 - 10)

Mean Size (201-300 Firms) Mean Cost (0 - 10)	Mean distance	Star (Net Benefit)	Strongly connected (Net Benefit)	Multi-Level (Net Benefit)
Mean	2.69	3,669.34	463,710.90	262,121.60
Median	3.00	2,387.16	308,558.60	154,509.40
STD	1.06	4,631.38	602,630.50	628,960.40
Max	4.00	22,856.17	3,069,430.00	2,667,548.00
Min	1.00	-1,994.10	-284,596.00	-829,966.00

Table 6.13 Mean Size(301 - 400 Firms), and Cost(0 - 10)

Mean Size (301-400 Firms) Mean Cost (0 - 10)	Mean distance	Star (Net Benefit)	Strongly connected (Net Benefit)	Multi-Level (Net Benefit)
Mean	2.46	6,143.43	1,086,392.00	690,955.90
Median	3.00	4,258.73	733,939.40	466,942.60
STD	0.92	6,450.86	1,172,756.00	1,204,708.00
Max	4.00	27,679.30	5,042,497.00	4,847,798.00
Min	1.00	-1,890.43	-375,345.00	-1,156,562.00

Table 6.14 Mean Size(401 - 500 Firms), and Cost(0 - 10)

Mean Size (301-400 Firms) Mean Cost (0 - 10)	Mean distance	Star (Net Benefit)	Strongly connected (Net Benefit)	Multi-Level (Net Benefit)
Mean	2.22	9,644.34	2,162,513.00	1,490,525.00
Median	2.00	7,737.05	1,628,261.00	943,873.20
STD	1.01	9,572.77	2,213,581.00	2,290,458.00
Max	4.00	40,668.54	9,976,725.00	9,692,558.00
Min	1.00	-2,945.90	-697,112.00	-2,001,978.00

6.5 Conclusion

Regardless of STP size, the main factor affecting the net benefit of knowledge sharing is the cost of knowledge acquisition. In this respect, the star model is the most efficient topology when the cost of obtaining and adapting knowledge (i.e. transforming knowledge into innovation) is high. The strongly connected model will perform better later on in STP development when costs are low, and the multi-level topology performs relatively poorly under all the conditions tested.

These findings support earlier work by (Lee et al., 2010) who recommended starting with a central organisation, which helps start-ups to innovate more. Then, maintain a good networking structure with other firms in the industry. Indeed the (Lee et al., 2010) model is similar to the star model introduced in this study where the central organisation can be a CI, or it can be, e.g. a tech-incubator. Here, the CI represents the state anchored model as presented by (Markusen, 1996), while tech incubators can be simulated using the DI (diversity innovation) number attached to transaction costs, a concept introduced by (Mellor, 2014; Mellor, 2015).

The strongly connected model simulated the case when all companies are in centric positions (similar to the hub-and-spoke model, when all firms are dominant) which Chiu (2008) reported being the best position for firms in innovation networks. Indeed, the simulations reported here confirm the efficiency of this topology, but also show that it is only the most suitable when costs are low. Indeed, if firms want to innovate more, they must incur some costs in order to be more centric. This topology may be attractive for mature firms, which have either started to generate money or have attracted investors.

While the multi-level connection may be the one most often used by a firm, it is advantageous to avoid this topology under conditions where knowledge sharing is expensive. Clearly, factors other than those discussed here may contribute to the capacity of a tech hub/cluster, for example, the space available, availability of venture capitalists (VCs) and proximity of related industries. Moreover, as the regression analyses in previous sections indicate, it is not possible to predict the optimal STP size using only the firms networking structure, which in turn is influenced by many factors. However, marginal effects like marginal gains and marginal costs could be added to future models to see if there is such a concept of an optimal size for an STP.

Generally, the findings in this chapter have both research and policy implications. First, they suggest that policymakers at the regional level should start by implementing a central organisation (CI) if they are following the "top-down" approach to STPs. Then, once the STP is well-established, they can let it move freely, possibly tending towards a strongly connected solution. However, a randomly connected model will be as beneficial as the strongly connected model when the "trust" network is well-built and has a cost close to zero. If this is not the case, then the model shows clearly that a CI "star" topology must remain in place to avoid excessive transaction costs without concomitant benefits, which is clearly a risky strategy.

Concepts such as ambidexterity (Benner and Tushman, 2015) may also be relevant, where an STP, surrounded by innovations and innovative firms wanting entry, has to decide on which innovations to implement. This is essential because not inviting new talent means that incumbents may proceed along a developmental path where on-cluster firms slowly enter a technology lock-in stage featuring few innovations, thus even in "non-star" structures, some form of CI is needed to steer the cluster in fruitful directions. If this is successful, then eventually large firms and MNCs will arrive, "fishing" for new talent and innovations. Thus, the next chapter will experiment on the role of ambidexterity and innovation distribution inside the business cluster in different environments.

Chapter 7: Innovation Distribution in Different Innovation Environments

7.1 Introduction

Previous chapters discuss business clusters success factors, which concluded that networking is the main determinant of cluster innovation. It shows that star structure is indeed the best structure at early stages of cluster development, while after passing the cut-off point, it is better to move into different topological structures. However, the previous chapter assumes that firms implement all incoming innovations, without taking into account any managerial decision-making capabilities, which is not the case. Moreover, it neglected the decision-making hierarchies' impact on net innovation income. Thus, this chapter aims to complement the story in previous chapters by evaluating the different organisation hierarchal structures under different innovation environment. Therefore, the Monte-Carlo simulation was used to simulate the three topological structures identified in the previous chapter using managers' quality check and random decision-making process as a control group.

Results show that it is very beneficial to have a central Cluster Initiative (CI) controlling the decision-making process in the early stages of cluster development where potential gains and losses are relatively modest. With maturity and with a high quality of decision–making amongst managers, then decisions are best taken by the CI with the individual on-cluster firms to ensure a high-growth trajectory. However, in environments abounding with poor-fit innovations, this becomes a high-risk strategy with high potential losses and indeed in this scenario, retaining a hierarchal (CI only) decision process is most helpful, even when the quality of decision–making amongst CI managers is poor. Next section introduces the used method, then results are discussed, the final section concludes.

7.2 Methodology

Monte-Carlo simulations (Chib and Greenberg, 1996) were performed in Matlab 2018R. Throughout it is assumed that managers choose innovations blindly from an initial portfolio of innovations containing projects with “negative” as well as “positive” consequences for organisational performance. Because they always a priori assume that their innovation will have positive consequences for corporate performance (whether this is true or not) or otherwise, that they can distinguish the quality of the innovation and make a “correct” decision. It is also assumed that “incoming innovation” is encapsulated in a business vehicle, i.e. the manager either adds or not, a new innovative firm (F) to the on-cluster group of firms.

Different decision-making methods were simulated based on the organisation structure using a Cellular Automata approach (Davis et al., 2007), similar to studies published previously (Mellor, 2014) and chapter 6. Simulations were performed when the organisational topology is based on one of the following:

Table 7.1 Overview of the Topologies Investigated

Number	The Topology Tested
1	Open network ("market structure") where firms are loosely connected to each other and each firm can invite other firms into the cluster based on their own judgment. This represents a control case to compare with other STP cases because it violates the most accepted definitions of STPs, but it can form a useful baseline, as shown in Section 7.2.1, (Equation 7.1 - Equation 7.3, Figure 7.3- Figure 7.5).
2	Start-up structure ("star topology") where all firms are connected to one CI and decisions are made unilaterally by the CI. This scenario also represents a baseline control and is shortly illustrated in section 7.2.2, (Equation 7.4 and Equation 7.6, Figure 7.6).
3	Start-up structure ("star topology") where all firms are connected to one CI and decisions are made by the firms and the CI collaboratively (CI and Firms, section 7.2.2, Equation 7.5 and Equation 7.7, Figure 7.7 and Figure 7.8).
4	Closed network (adhocracy, a strongly-connected model, section 7.2.3), this is represented by any two firms jointly making a decision without involving the CI (Equation 7.8 and Equation 7.10, Figure 7.11 and Figure 7.12).
5	The ambidextrous organisation, operating within a strongly-connected model, where a joint decision is made by any two firms and then the CI (Equation 7.9 and Equation 7.11, Figure 7.9 and Figure 7.10) in section 7.2.3.

For each of the above, the quality of the decision-making at the managerial level was varied between:

1. Managers make decisions randomly i.e. 50:50, as in flipping a coin.
2. The managers always make the right decision.
3. The managers can make decisions with a degree of accuracy between 50% and 100%. (The case of managers making decisions with between 0% and 50% accuracy was omitted from this work because this could be a scenario for, e.g. state institutions, but not for the business cluster).

The different scenarios were used at the aggregate level, which reflects the overall innovation at cluster level because of the assumption that cluster innovation is the total of the innovation of the firms inhabiting the STP. Thus, STP success is the total net benefit gained by all actors. The different types of innovations were evaluated using equations (7.1 – 7.11) in sections 7.2.1 – 7.2.3.

7.2.1 Open network business cluster structure (market structure)

In this case (Table 7.1, number 1), the STP includes firms, which are not connected to each other, and each firm implements its innovation independently of CI or other firms. Then, the quality of management decisions is simulated with the parameter $(q_{m,i})$, where for F managers it is between (0.5 and 1.0) and randomly generated from uniform distribution, so that if $(q_{m,i} < 0.75)$ indicates that a manager with a medium quality of decision, who most likely makes 50:50 random decisions (as in flipping a coin). Otherwise, they are of very high quality and will make the right decision (i.e. accepting good innovations and rejecting bad innovations). A vector of (n) element was then generated representing all managers in on-cluster firm level (F1, F2, etc), where each manager is different from any other in both decision-making capabilities, and the cash value of innovations generated. Random decisions are simulated with the value (d_i) which is between (0 - 1) generated from the uniform distribution and indicates that if $(d_i > 0.5)$ meaning a positive decision and accepting the innovation regardless of the actual outcome (positive or negative). For each run, a new number of firms (n) is generated, which enables us to control for the role of cluster size.

Using the open network structure, the following cases were simulated:

i. On-cluster firms implement an innovation independently of CI and of any managers, so any incoming project can be implemented. This case is implemented as a control experiment for comparison purposes with other cases.

So, no quality checks are done in this case and no control for random decisions. In this case, the net innovation cash flow for all firms (b) is calculated using Equation 7.1, where $Innov_i = I_i - C_i$ and I_i is the innovation outcome cash value, and Ci is the cost of implementing that innovation:

$$\boldsymbol{b = \sum_{i=1}^{n} Innov_i \text{ , } b \text{ is the net total innovation, } Innov_i \text{ is the incoming innovation project value for firm } (i)}$$

Equation 7.1: Open Network Net Innovation

ii. The managers of on-cluster firms decide. If they have excellent decision-making skills $(q_{f,i} > 0.75)$ - where $q_{f,i}$ is the quality of the decision making - then they only implement good innovations $((Innov_i - TC_i) > 0.0)$, TC_i is the decision making cost (transaction cost). Otherwise, innovation is rejected. Where their decision-capacity is of average quality, then they only approve the innovation if $(d_i > 0.5)$, regardless of the value of the innovation (see Equation 7.2):

$$b = \begin{cases} \sum_{i=1}^{n} Innov_i - TC_i, if\,(q_{f,i} > 0.75) \text{ and } (Innov_i - TC_i) > 0) \text{ or } (d_i > 0.5) \\ b - TC_i, if\,(q_{f,i} > 0.75) \text{ and } (innov_i - TC_i) < 0) \text{or } (d_i < 0.5) \end{cases}$$

Equation 7.2: Checks at Firm Level

iii. Then, the quality of decisions made is not checked, meaning that F managers will only approve if $(d_i > 0.5)$ regardless of the value of the innovation (random decisions). This is summarised in equation 7.3:

$$b = \begin{cases} \sum_{i=1}^{n} Innov_i - TC_i, if \;\; (d_i > 0.5) \\ b - TC_i, if \;\; (d_i < 0.5) \end{cases}$$

Equation 7.3: Random Decision by Firm Managers

7.2.2 Start-up structure (star topology)

In this case, business cluster firms are connected to the central organisation called Cluster Initiative (CI), which act as control agency helping firms connecting with VCs and build internal relationships as well as coordinating activities and innovations. The baseline control (Table 7.1, number 2) assumes a stable functioning steady-state STP scouting for innovations examines 100 innovations each worth 100 Monetary Units (MU), and in this case, the costs for implementing a decision are fixed for the purposes of illustration to 20 MU and the decision-making costs to 2 MU. Table 7.2 briefly shows that even with 100% dependable decision-making by CI managers, the returns are dependent on the quality of the innovations presented to that business cluster.

Table 7.2 Returns From 100 Innovations Each Worth 100 MU Where the Innovations are of Varying Quality and Presented to a CI Management with 100% Correct Decision-Making Ability

Percent of "good" innovations	Return (MU)
100	7800
50	3800
0	-200

Moving to the case of Table 7.1, number 3, the mean (average) quality of the F decision-makers checking the innovation must be greater than the cut-off point (0.75) $(mean(q_{m,i}, q_{f,i}, q....) > 0.75)$, and this figure is reached because at this point two good quality F managers can overcome the poor decision of a third F one. However, this cannot happen without cost (e.g. discussion times), which is in this simulation is obtained randomly for each firm (from a uniform distribution) with a value of $(0 \le TC_i \le 100)$, and the value of a beneficial innovation value is simulated with $(-1000 \le Innov_i \le 1000)$ MU, meaning that an innovation with the value $(Innov_i \le 0)$ is a poor innovation.

In contrast, the decision-making quality at CI level was given a random constant quality because as shown in Figure 7.1, the quality of CI decisions applies to all other on-cluster firms indiscriminately (i.e. it does not change according to the number of firms in the STP). The CI quality was given the value $(0.5 \le q_c \le 1)$, so each time new innovation has to be considered this can change between $(0 \le CI_i \le 1)$ and $(CI_i < 0.5)$, the latter indicating a probable rejection (regardless of if the outcome would have been positive or negative). Figure 7.1 shows the science park organisation, where each firm is connected to the central organisation CI, in a star topology reflecting the state-centred cluster organisation.

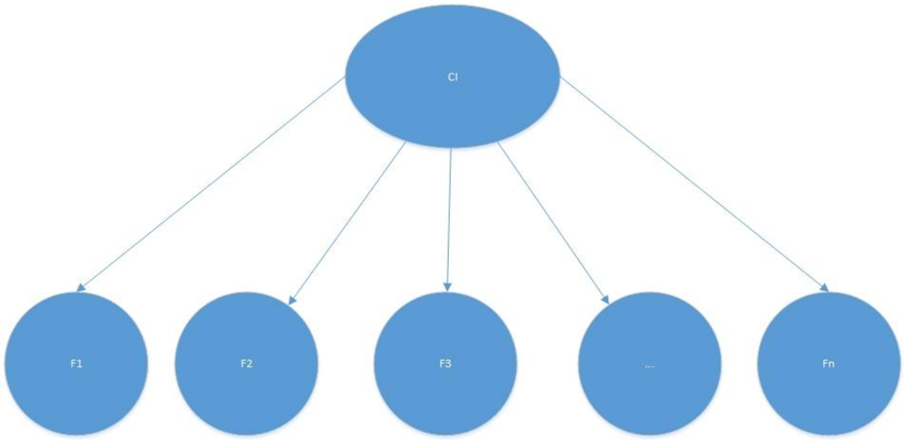

Figure 7.1 Science Park Organisation (star topology)

Using organisation structure in figure 7.1, there are four different scenarios for types of decision-making:

i. Similar to Table 7.1, number 2, incoming innovations are evaluated by CI, and a decision depends on the decision-making quality within the CI, so if the quality is high $(q_c > 0.75)$ the innovation will be implemented if $((Innov_i - TC_i) > 0)$ resulting in positive cash flow. Otherwise, innovation is not approved. On the other hand, if CI managers are of average quality, then the innovation will be implemented if $(CI_i > 0.5)$, where CI$_i$ represents a random decision made by CI management. See equation 7.4:

$$\boldsymbol{b} = \begin{cases} \sum_{i=1}^{n} Innov_i - TC_i, if(\, q_c > 0.75)\ and\ (Innov_i - TC_i) > 0)\ or\ (CI_i > 0.5) \\ b - TC_i, if\ (q_c > 0.75\ and\ (innov_i - TC_i) < 0) or\ \ (CI_i \leq 0.5) \end{cases}$$

Equation 7.4: Decision by CI Managers with Quality Checks

ii. Incoming innovations are evaluated by both the F manager of the on-cluster firm responsible as well as the CI. In the first case star topological structure is taken, and the quality of the decision is calculated as the mean of both managers quality, meaning firstly that if the mean quality is below the cut-off point, then an approval of both managers must be obtained, which in turn involves doubling the transaction costs, as given in the following equation 7.5:

$$b = \begin{cases} \sum_{i=1}^{n} Innov_i - 2 \times TC_i, if\left(\mu(q_c, q_{f,i}) \right) > 0.75 \; and \; (Innov_i - 2 \times TC_i) > 0) \; or \\ \quad ((d_i > 0.5) and \; (CI_i > 0.5)) \\ b - 2 \times TC_i, if \; \left(\mu(q_c, q_{f,i}) \right) > 0.75 \; and \; (innov_i - 2 \times TC_i) < 0\big) or \\ \quad \big((d_i < 0.5) \; or \; (CI_i < 0.5)\big) \end{cases}$$

Equation 7.5: Decision by F1 and CI with Quality Checks

iii. In the third case, there will be no quality checks. Consequently, implementing any innovation projects approval is done by the CI and depends on the approval value of the CI, so if $(CI_i > 0.5)$, then the innovation will be implemented. Otherwise, it will be rejected. It is assumed that the decision will change between different firms over time. This is summarised in the following equation 7.6:

$$\boldsymbol{b} = \begin{cases} \sum_{i=1}^{n} \boldsymbol{Innov_i - TC_i}, \quad \boldsymbol{if(\,CI_i > 0.5\,)} \\ \boldsymbol{b - TC_i, if \; (\,CI_i < 0.5)} \end{cases}$$

Equation 7.6: Random Decision by CI

iv. In the last case, the check is done by both the F managers and CI managers. However, the approval of both managers (using logical "and" operation) must be obtained. On the other hand, the transaction cost will be doubled as it needs checking from two managers, and even if the second check would take less time, but two managers will still be involved. This is simulated using the following equation 7.7:

$$b = \begin{cases} \sum_{i=1}^{n} Innov_i - 2 \times TC_i, if \;\; ((d_i > 0.5) and \; (CI_i > 0.5)) \\ b - 2 \times TC_i, if \;\; ((d_i < 0.5) \; or \; (CI_i < 0.5)) \end{cases}$$

Equation 7.7: Random Decision by F1 and CI Manager

Next, the different decision-making process scenarios applied when having a strongly connected STP topology are discussed.

7.2.3 Closed network (Strongly connected: adhocracy and ambidextrous)

In the third case, the cluster organisation structure modelled consisted of a closed network (strongly-connected model) organisation where the decision will be discussed between two on-cluster firms making decisions (Table 7.1, number 4) or two on-cluster firms with the CI (Table 7.1, number 5), illustrated in figure 7.2. The simulations involved:

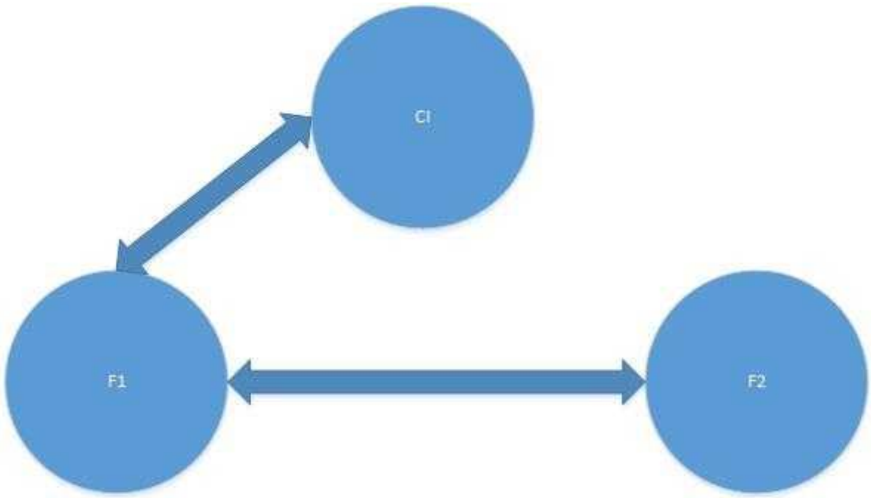

Figure 7.2 Strongly-connected with CI

i. In the first case, the decision is discussed between the two F managers at F1 and F2 collaboratively (Figure 7.2). Similar to previous cases, the quality of both F managers is the mean quality of both F managers, and if that exceeds the cut-off point, then they will make the right decision. Otherwise, introducing innovation will need both managers approval. This is simulated using the following equation 7.8:

$$b = \begin{cases} \sum_{i=1}^{n} Innov_i - 2 \times TC_i, if(\ \mu(q_{m,i}\ , q_{f,i}\ ) > 0.75\ and\ (Innov_i - 2 \times TC_i) > 0)\ or\ ((d_i > 0.5) and\ (d_j > 0.5)) \\ b - 2 \times TC_i, if\ \left(\mu(q_{m,i}\ , q_{f,i}\ ) > 0.75\ and\ (innov_{ci} - 2 \times TC_i) < 0\right) or\ ((d_i < 0.5)\ or\ (d_j > 0.5)) \end{cases}$$

Equation 7.8: Decision by F1 and F2 with Quality Check

ii. The second case controls if the CI is involved in the decision-making process. In that case, the quality of the decision will be the mean of the three decision-makers. Otherwise, the decision is approved if it gets approved by the three managers. Of course, the check cost (transaction cost) will be different from other cases. However, the assumption is that it will be triple the actual check cost. This is more of a tree hierarchal structure. This case was modelled using the following equation 7.9:

$$b = \begin{cases} \sum_{i=1}^{n} Innov_i - 3 \times TC_i, if\left(\mu(q_c, q_{m,i}, q_{f,i}) > 0.75 \; and \; (Innov_i - 3 \times TC_i) > 0 \right) or \\ \left((d_i > 0.5) and \; (d_j > 0.5\right) and \; (CI_i > 0.5 \\ )) \\ b - 3 \times TC_i, if \; (\mu(q_c, q_{m,i}, q_{f,i}) > 0.75 \; and \; (innov_i - 3 \times TC_i) < 0) or \\ \left((d_i < 0.5) \; or \; (d_j > 0.5\right) or \; (CI_i < 0.5)) \end{cases}$$

Equation 7.9: Decision by F1, F2 and CI with Quality Checks

iii. The same cases were then simulated, but without looking into the quality of the decision-makers, assuming that decisions are made randomly, which enables us to distinguish between having high-quality decision-makers and coin-flipper decision-makers in a hierarchal cluster model. Thus, when the decision is discussed between the two F managers at F1, and F2 (Figure 7.2). Similar to previous cases, to introduce in innovation will need both managers approval. This is simulated using the following equation 7.10:

$$b = \begin{cases} \sum_{i=1}^{n} Innov_i - 2 \times TC_i, if \; ((d_i > 0.5) and \; (d_j > 0.5)) \\ b - 2 \times TC_i, if \; ((d_i < 0.5) \; or \; (d_j > 0.5)) \end{cases}$$

Equation 7.10: Random Decision by F1, and F2

iv. Then, it controls if the CI is involved in the decision-making process. In that case, the decision is approved if it is accepted by the three managers. Then, the check cost will be triple the actual check cost. This case is modelled using equation 7.11.

$$b = \begin{cases} \sum_{i=1}^{n} Innov_i - 3 \times TC_i, if \left((d_i > 0.5) and \; (d_j > 0.5\right) and \; (CI_i > 0.5)) \\ b - 3 \times TC_i, if \; \left((d_i < 0.5) \; or \; (d_j < 0.5\right) or \; (CI_i < 0.5)) \end{cases}$$

Equation 7.11: Random Decision by F1, F2 and CI

7.3 Results

7.3.1 Open network ("Market" structure)

The results for scenario (Table 7.1), number 1, illustrate perhaps unsurprisingly that in this case, the best outcomes occur when high-quality decisions are made by firm (F) managers, while random decisions give rise to outcomes that are not as favourable, although the best-case scenarios do not show huge differences between firms with high-quality F managers and firms which implement any upcoming innovation. Correlation analysis of the quality of decisions showed a moderate correlation of around 0.110 and p-value of less than 0.001. Thus, the size (number of firms) and the average innovation income from project initiatives (Table 7.4) were compared and found that the size of the cluster does not have any impact when there is no control at all, not even random 50%. However, it does positively impact overall levels of innovation when F managers exhibit high decision-making quality and are negative when F managers are coin flippers (50:50). Figures 7.3-7.5 show the relationship between the number of firms in a cluster and the net innovation income, showing the random relationship between cluster size and net innovation in the absence of quality control (figure 7.3), while it is negative when decisions are random (figure 7.5), and positive when quality checks are available (figure 7.4). Moreover, it highlights that if STP accepts any incoming innovation, then the main determinant is the average innovation cash value. But because it is not possible to have good innovations all the time, the indication is that this unstructured "market" approach should be avoided.

Table 7.3 Descriptive Statistics of Different Decision-Making Configuration

Decision making procedure	N	Minimum	Maximum	Mean	STD
No Check	5,000.00	-40,798.00	40,180.00	47.42	9,251.95
Check by Firm(with quality control)	5,000.00	-13,014.00	53,329.00	9,608.89	9,455.28
Random Decision by Firm	5,000.00	-46,945.00	23,537.00	-6,268.25	8,536.72

Table 7.4 Pearson Correlation (Open Network Topology)

	No Check	Check by Firm(with quality control)	Random Decision by Firm
Average Innovation	0.656**	0.322**	0.349**
NOF	0.007	0.579**	-0.408**

** Statistically significant at 99%

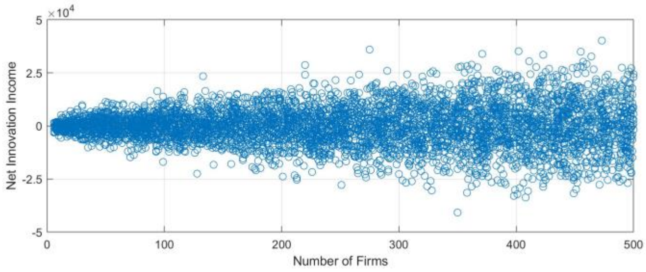

Figure 7.3 Open Network, firms implementing any incoming innovation VS the number of firms inside the business cluster

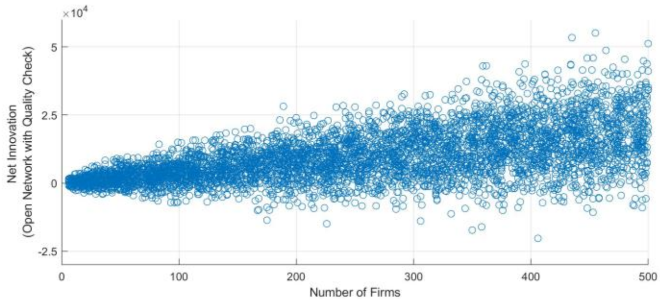

Figure 7.4 Open Network, Firms implementing incoming innovation based on Firms Managers Quality and Value of the Incoming innovation VS number of firms inside the business cluster

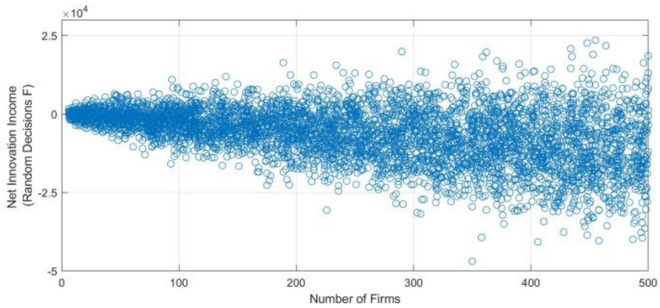

Figure 7.5 Open Network, Firms implementing incoming innovation based on a random decision made by firms' manager VS number of firms inside the business cluster.

7.3.2 Start-up structure (Star topology)

This section deals with the situations in Table 7.1, numbers 2 and 3, i.e. a "star" start-up structure when a CI is involved. The different cases investigated are:

i. Decisions are made by CI, and CI quality is checked.
ii. Random decisions are made by CI management.
iii. Collaborative decisions are made by CI and F management with quality checks.
iv. Random collaborative decisions by CI and F management.

Table 7.5 Descriptive Statistics Star Topology

	N	Minimum	Maximum	Mean	Std. Deviation
Check by CI (with quality control)	5,000.00	-41,352.00	129,583.00	9,839,03	33,080.00
Check by CI and Firm (with quality control)	5,000.00	-58,022.00	63,431.00	-4,435.28	15,575.27
Random Decision by CI	5,000.00	-41,352.00	25,242.00	-6,239.06	8,535.59
Random Decision by CI and Firm	5,000.00	-64,590.00	16,571.00	-12,529.71	11,940.63

Table 7.5 presents descriptive statistics of star topology structure showing that in the worst-case, all decisions making scenarios are – almost – equivalent. This is because in an environment with many negative innovations even coin-flipping managers avoid expensive mistakes to almost the same extent as discriminating managers do. Best-case occurs when CI managers have a high quality and decide alone, the reason being that collaboration between CI managers and F managers (which is also good) also doubles the transaction costs, thus detracting from the final value.

In order to understand the impact of different factors in each of the decision-making scenarios, the correlation analysis was controlled between average firms' innovation, average check cost, number of firms and the final net innovation values obtained (Table 7.6).

Table 7.6 Correlation Analysis Star Topology and Average Innovation, Check Cost, and Number of Firms

	Average Innovation	Average Check Cost	Number of Firms
Check by CI (with quality control)	0.075**	-0.130**	0.146**
Check by CI and Firm (with quality control)	0.110**	-0.476**	-0.184**
Random Decision by CI	0.362**	-0.417**	-0.422**
Random Decision by CI and Firm	0.144**	-0.600**	-0.599**

**** Statistically significant at 99%**

Table 7.6 shows that in the case of random decisions net innovation is mainly impacted by the number of firms (negatively), average firms' innovation (positive), and check cost (negative). However, in case of decision making with quality check, these factors had mainly moderate to low impact (figures 7.6 – 7.8). However, the impact of managerial decision-making on net innovation (in the case of quality check), showed a very strong correlation (the net total innovation 0.744 and the quality of CI managers 0.633), indicating the major role that is played by qualified managers, a finding apparently confirmed when increasing the number of firms (thus also increasing the number of managers). However, when comparing decision-making by the CI only and by the CI and F-managers in the star topology (where firms communicate over the CI), any positive effect is counteracted by the increased transaction costs, table 7.6 showing a low negative value. This underlines that in start-up conditions (as well as under conditions of negative innovation environment) the hierarchical star topology is always most efficient.

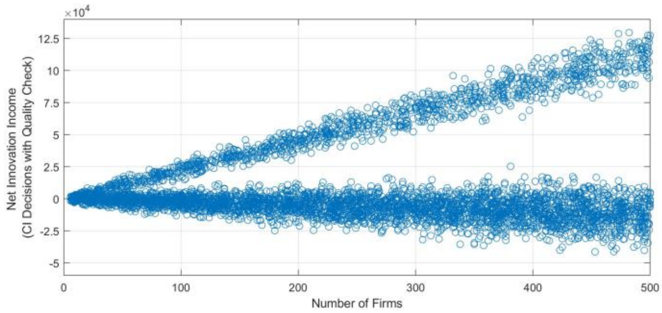

Figure 7.6 Star Topology, firms implementing incoming innovation based on the CI managers quality of decisions making VS number of firms

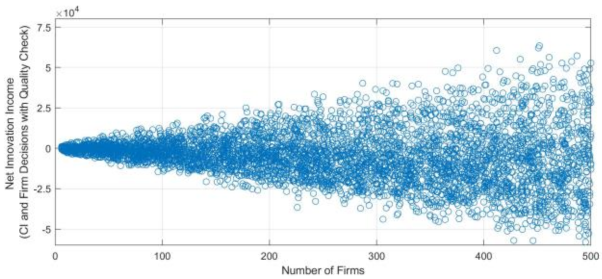

Figure 7.7 Star Topology, firms implementing innovation based on the quality of its own managers and CI managers VS number of firms

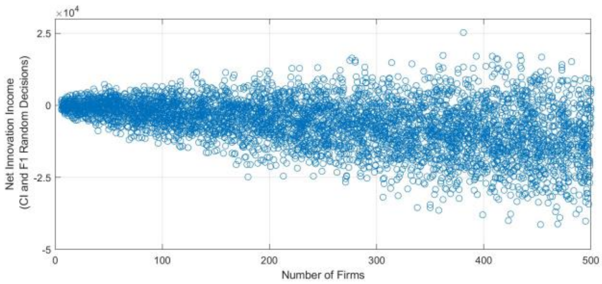

Figure 7.8 Star Topology, a random collaborative decision between CI managers and firms' managers VS number of firms

This indicates, as before, that there is little difference between qualified and none-qualified managers in environments with many bad innovations. It also implies these could be scalability issues in the "star" model when expanding the STP if there is not a concomitant increase in the CI.

7.3.3 Closed network (strongly connected: adhocracy and ambidextrous)

In this scenario (Table 7.1, numbers 4 and 5) decision are made by F managers (especially by neighbouring firms in the architecture, representing two networked inhabitants making decisions collaboratively) with and without the CI, and thus the range of alternatives are:

i. A decision is made jointly between two F managers, where the quality of both F managers is controlled for (Table 7.1, number 4, Figure 7.11).
ii. A random decision is made by two F managers (Table 7.1 number 4, Figure 7.12).
iii. A random decision is made by CI managers together with two neighbouring F managers (Table 7.1, number 5, Figure 7.10).
iv. A decision is made between two firms collaboratively with CI managers with quality checks (Table 7.1, number 5, Figure 7.9).

Results are presented in Table 7.7 which shows that in the worst cases scenarios, the values for the minimum net innovation values (the column named “minimum” in table 7.7) are approximately similar, for example, the difference between decisions made by qualified F managers (two firms), and non-qualified F managers (two firms), is not very high, around 10,000. Conversely, the difference between an ambidextrous organisation with qualified managers and random decision-makers is 4,565, indicating clearly that in the worst-case scenario, more hierarchies will reduce the difference between qualified “good” managers and random decision-makers.

Moving on from the worst-case scenarios there is a perhaps unsurprising gain from having qualified F managers and CI managers, even though the transaction costs will be doubled when CI is involved together with F managers (with quality-check). Nevertheless, it is under these conditions that the value gain is highest. This represents the “ambidextrous” situation (Table 7.1, number 5) and would be the preferred scenario during times of expansion and scaling up the STP not only because the higher quality of decision-making will better shape the selection and intake of new innovative firms, but also because it would spread the use of resources and help prevent over-straining the CI. In more detail; figures 7.9 - 7.12 show the negative impact of growing the STP (this effect is due to the increasing transaction costs) however this negative tendency diminishes when quality control is added (figures 7.9 and 7.11).

Table 7.7 Descriptive Statistics Strongly-Connected Model

	N	Minimum	Maximum	Mean	Std. Deviation
Check by Two Firms (with quality control)	5,000.00	-46,757.00	28,682.00	-4,684.05	10,091.34
Check by Two Firms and CI (with quality control)	5,000.00	-80,394.00	54,878.00	-11,835.29	17,305.20
Check by Two Firms (without quality control)	5,000.00	-59,252.00	14,974.00	-12,584.96	11,877.17
Random Decision by Two Firms and CI	5,000.00	-84,959.00	13,495.00	-18,768.45	16,767.01

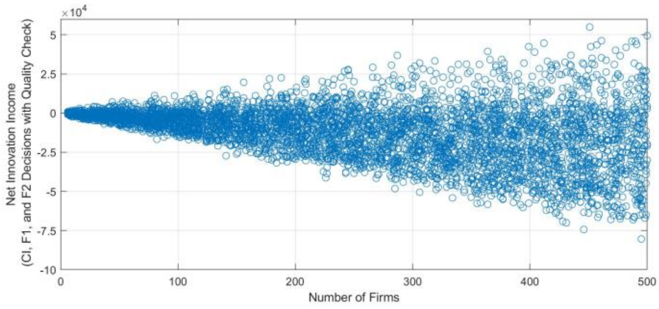

Figure 7.9 Ambidextrous Organisation, (F1, F2, and CI) collaborative decision making with quality check VS number of firms.

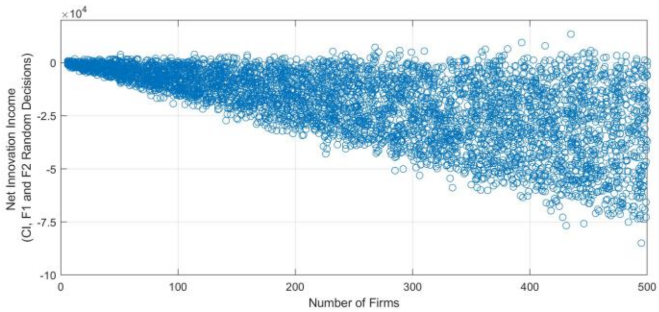

Figure 7.10 Ambidextrous Organisation, Random collaborative decision by (F1, F2, and CI) VS the number of firms.

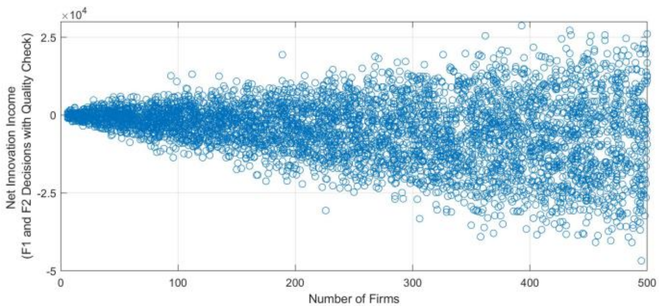

Figure 7.11 Ambidextrous Organisation, Collaborative decisions of (F1 and F2) with quality check VS the number of firms.

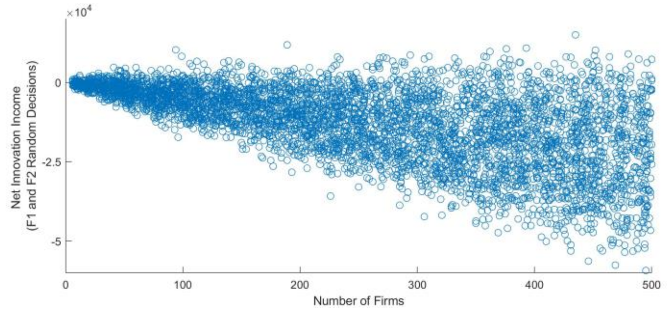

Figure 7.12 Ambidextrous Organisation, Collaborative random decisions of (F1 and F2) VS number of firms.

7.3.4 Comparing different cluster topologies

Sections 7.3.1 – 7.3.3 discussed simulation results obtained by using different STP topologies under different decision-making conditions and best-case results are shown in Table 7.8.

Table 7.8 Best Cases in all three topologies

Topology	Best Case	Optimal NOFs	Optimal Check Cost	Optimal Average Innovation Income	Net Innovation
Open Network	Checked by Firm with Quality Control	314.00	5.16	49.12	53,329.00
Star Topology	Check by CI (with quality control)	482.00	1.48	33.41	132,316.00
Strongly Connected Topology	Check by Two Firms and CI (with quality control)	451.00	2.03	36.96	54,878.00

Table 7.8 presents the best cases in all the three different business cluster structures combined with the optimal number of firms, innovation income and check the cost. It shows that the best outcomes occur when there is a quality check at either F or CI level. Table 7.8 indicates that the star topological structure is the best for achieving the highest return on incoming innovations, which is because of lower costs, i.e. a lower average innovation can achieve higher returns when decisions are centralized, although this may break down when the STP becomes significantly larger and, in agreement with the results of Al-kfairy et al (2019a) the strongly connected model would be advantageous at this point.

A comparison of different cluster topologies under worst-case conditions is shown in Table 7.9. It confirms that all worst-case scenarios occur when decisions are randomly made, and the average income is quite low. The most damaging scenario is encountered when innovations of low average value encounter an open (market) network topology, which allows harmful innovations to proliferate without any embargo from the CI. Overall in the two other topologies, the least-worst case is when innovation approval is happening at F level with qualified F managers and the worst-worst case when random decisions are made at the three levels (two F and CI), which is due to increased decision costs.

Table 7.9 Worst Cases in Three Topologies

Topology	Worst Case	NOFs	Check Cost	Average Innovation Income	Net Innovation
Open Network	Random Decision by Firm	350.00	35.20	-116.57	-46,945.00
Star Topology	Random Decision by CI and Firm	495.00	49.86	-0.53	-64,590.00
Strongly Connected Topology	Random Decision by Two Firms and CI	495.00	49.86	-0.53	-84,959.00

7.4 Conclusion

This study complements previous studies focused on the role of networking in innovation development and knowledge spillover (Cowan et al., 2007; Bathelt et al., 2004; Bell, 2005; Zhang et al., 2017)), and studies on the role of CI management [e.g. (Ruiz et al., 2017; Klofsten et al., 2015; Sotarauta, 2010)]. However, as Nobel laureate Joseph Stiglitz points out, management structure determines organisational profitability [e.g. (Sah and Stiglitz, 1985)]. Thus, we go further by adding the dimension of organisational structure into the debate, as well as exploring the quality of decision-makers at both F and CI levels under differing innovation regimes.

Three different types of networks: open (market), star (hierarchy), and closed strong (adhocracy in start-up phase, proceeding to ambidextrous) networks [see (Cowan et al., 2007)] were investigated, and the results are in some respects broadly in agreement with previous studies. An open (market) model may, for example, include property-related services like the provision of infrastructure and most commonly utilized services (Salvador, 2011), encompassing conference and meeting rooms, restaurant and cafeteria, as well as more specialised facilities e.g. biowaste incinerator and chemical storage, where appropriate (Rowe, 2014). In this structure, barriers to entry are low, poor-fit firms can inhabit the STP, and "bad" innovations can abound unchecked. This scenario may benefit from establishing a CI with a clear vision for the future direction for the STP.

The star (hierarchy) and closed strong (adhocracy, ambidextrous) models both contain a strong CI. The results presented here underline the crucial role played by the CI in sustaining and developing an STP at the start-up stage and into early maturity. However, where this study differs from others is that the results presented here show that one is not a progression from the other, rather they are different developmental trajectories that are pre-determined early on by the form of corporate organisation chosen.

Clearly, one starting point could be a costly large project, probably state-supported and especially if large firms can be persuaded to participate, then a closed strong model may predominate and be successful. However, this is a risky strategy because the size of the catchment area, in terms of potential inhabitants, is a broad research gap, as are other important but unknown factors, e.g. what are acceptable churn rates amongst inhabitants?

Another scenario is a new small start-up, and in this case, the star (hierarchy) model is most suitable due to low transaction costs. Under certain circumstances, this model can progress to an ambidextrous model but should be retained in environments where the catchment is modest, and growth cannot be expected. Although these analyses support the views of Chen et al. (2006), Albahari (2015) and Albahari et al. (2018) in that the quality of the CI management team can be positively related to STP performance. The results presented here underline that a CI is also of benefit where the quality of CI decision-making is poor, and the environment has relatively few suitable innovations or many poor-fit potential inhabitants. Indeed Table 7.2 shows a precarious situation where losses can be incurred even in steady-state, so the CI could be especially important in a situation where the STP is a start-up, and the on-cluster firms are also inexperienced start-ups.

In an analysis of a large mature STP, Al-kfairy et al. (2019b) observed that part of the STP demographic consists of micro-firms and many of these leave the STP after 4-5 years, and also a tendency for firms achieving a size of 100-120 employees to leave after 15-17 years. So, STPs do need to continually choose new inhabitants both for corporate performance but also – more importantly – to refresh the innovation base of the whole cluster and avoid “lock-in” with old technology. Choosing new innovative inhabitants is inherently risky. The results presented here show that concepts of “business ambidexterity” [see (Benner and Tushman, 2003; Benner and Tushman, 2015; O'Reilly III and Tushman, 2013)], can be extended to clusters of firms, in this case, STPs. However, there are unexpected differences between STPs and single organization; Will et al. (2019) showed that for spreading innovations inside an organization, multiple layers of F managers making decisions at close to coin-flipping (50:50) efficiency were still beneficial because at each decision round moving up the hierarchy 50% of expensive "bad" innovations were removed. In contrast, in the STP case, increasing the number of hierarchies showed a negative impact even when decision-making was good at both CI and F levels, and this is due to increased transaction costs negating the advantage gained. Put simply, a firm co-locating to an STP entails a larger slice of costs than departmental decisions inside a firm. Ambidexterity, however, still has a place as the STP develops and strong inter-firm connections are formed, whereupon ambidextrous decision-making can be shared between the CI and others, and this has a knock-on effect that the CI can remain compact and cost-competitive as the STP reaches full maturity. To reach this outcome, the CI can include those managers at F level who are experienced and skilful decision-makers, and this, in turn, underlines the importance of STPs of attracting large firms. Start-up STPs are filled with innovative small firms. Moreover, this situation (at an appropriate stage) can attract larger firms that do not want to miss out on these new innovations (perhaps by acquiring the aforesaid small innovative firms). These larger firms can contribute experienced F managers to co-operate with the CI in making decisions, but the timing of the transition from the star model to ambidextrous will be fraught, and from the overview presented in the introduction to this paper, only one in five STPs will achieve this situation.

Chapter 8: Thesis Conclusion

8.1 Summary of the Results

The aim of this section is to summarise cluster contribution into regional development as well as its success factors discussed in (Chapter 4 and Chapter 5:). Then, summarise findings on cluster organisation structure contribution to knowledge spillover at different development stages (Chapter 6: and Chapter 7:).

This thesis took a well-established business cluster case study to investigate its contribution to the overall regional development and empirically extract factors contributed to its success for over 30 years of development. At the aggregate level, results show that business clusters' generally foster more innovation compared to firms located outside the business cluster and spend more on R&D investment than off-cluster firms confirming that business clusters attract more VCs investment. Socialising and networking are other factors distinguishing on-cluster firms from off-cluster firms. However, financially, both firms located on-cluster and off-cluster grow albeit that SMEs are the dominant on-cluster, while off-cluster firms are mainly micro firms.

At the micro-level, using the conceptual model of success indicators produced in Figure 3.1 and Figure 3.2, success factors were extracted. Results prove that cluster development is not linear, and many factors can impact its development. Firms' growth measured as growth in its size, turnover and innovation capabilities show the important role of firm maturity (measured as its age), which impact both size and financial development of cluster firms. It shows that being part of a business cluster helps firms to grow at its early development stages, but after a while cluster, age will have a negative impact. However, it proves that continuous innovation, shareholders' as well as R&D investment would help firms overcome the age impact. This highlights the importance of having investment bodies (VCs) connected to a business cluster either directly or through CI. On the other hand, networking was discovered as the main factor influencing cluster innovation measured as social expenses ratio to turnover, which underlies the crucial role played by networking to achieve a higher innovation output.

In order to find out if these factors are different based on firms' location, it was then compared with firms located outside the business cluster (which was the control group). Results confirmed the location impact on cluster firms by showing that different factors influence off-cluster firms' group than the on-cluster one. Off-cluster size is positively influenced by firm age as well as shareholder contribution, while networking has a negative impact on its development, albeit that age and shareholder contribution is very low compared to the on-cluster ones. Financially, off-cluster firms' are impacted by firms size (quadratic), age (linear, but negative), and a positive of R&D growth, however, it shows that these factors impact is very low compared to on-cluster firms group, which is further confirmed by evaluating factors contributing to off-cluster firms innovation.

Generally, results of Chapter 4: and Chapter 5: prove that being located inside a business cluster makes a difference in both firms' development as well as the factors influencing its development, which contributed in understanding the location impact on firms development. Moreover, while all success factors impact understood, socialising and networking needed further analysis since it is impacted by how firms are organised inside a business cluster. Therefore, this thesis extended business cluster understanding by analysing different cluster topological structures in Chapter 6: and Chapter 7. They help in to understand the impact of cluster organisation on knowledge spillover and thus innovation distribution.

Chapter 6 shed lights on the importance of selecting the right cluster topological structure at the right cluster development. It shows that it is very beneficial for a business cluster to start as star topology where all firms are connected to one central organisation, which helps to eliminate overhead networking costs. However, it does not guarantee a high innovation return compared to a strongly connected model or even randomly connected model which is recommended after passing early cluster development. These results neglected the role of managerial qualities on decision making, which is further discussed in chapter 7. Thus, chapter 7 complements earlier results by introducing two concepts into chapter 6 and build on author's contribution [see (Will et al., 2019)], which include 1) not all innovation is guaranteed to be good (positive outcome) and 2) implementing incoming innovation depends on managerial decisions of adapting that innovation or rejecting it. However, evaluating incoming innovation depends on managers quality of making the right decisions. Again, results show the superiority role of CI and its qualified managerial bodies in achieving higher innovation outcome. This is helpful, especially when a business cluster is still small. However, when a business cluster scales up, it becomes very hard for CI to control its inhabitant's development. Consequently, it is crucial to move the decision-making process to firm-level or two neighbouring F-level managers. However, adding an extra layer of managers will indeed increase the transaction cost, and reduce the innovation benefits albeit that it may increase the possibility of making the right decision especially if the managers possess high-quality of decision-making.

Interestingly, coin-flipping managers who make random decisions can be helpful in eliminating bad innovations through hierarchies. Thus, hierarchies can be good if a cluster inhabitant is almost bad innovators. Nonetheless, business clusters are not supposed to host bad innovators. It should only consider good innovators through a well-defined evaluation mechanism or graduation mechanism. This is especially applicable if the business cluster includes incubation programme, where incubated ideas may graduate into the business cluster. Figure 8.1 summarises the high-level business cluster success factors.

Generally, this research suggests that business cluster can help firms to produce more innovation, however, it proves the importance of managers quality at all levels and the role of cluster organisation structure in adapting incoming innovation. It indicates that business cluster does not automatically mean more innovation or better finincail behaviour of the firms, and there are other conditions for stimulating firms performance. Although previous researche handle the role of networking in innovation distribution and how this networking is stimulated by business clusters [see 2.4.1 and 2.5], this study adds into the current state-of-the-art knowledge by understanding how cluster organisation structure contributes into knowledge spillover and thus the overall innovation benefit outcome. The thesis helps identifying the importance of knowledge adaptation cost and networking cost when selecting cluster organisation structure. This thesis proves thar star toplogical structure with experienced CI managers at early stages of cluster development is the most suitable organisation structure, then once cluster moves into more mature stage and knowledge is well-established they can move into other topological structure. Indeed, this thesis conclusion fits with early cluster research as it proves that cluster networking is the most important actor in achieving the higher innovation output, however, this is under certain conditions which was not handled in earlier researches, those conditions can be summarised as:

1. Selecting the right cluster organisation structure which minimise the networking cost and maximise the benefits.
2. Reducing the knowledge aqusation costs.
3. Selecting the right experienced CI managers.
4. Train firms manager to select the right innovation.

Moreover, the thesis results suggests some business cluster limitations, such as firms aregrowing up to a certain age and size, which indicates that on-cluster firms, even in a very successful business clusters will not linearly grow. However, this may indicate that business cluster may have size limitation, or firms graduate after to growing into a certain size, but the reason behind this graduation is a future research.

In conclusion, this thesis has both policy and research implications. Next section discusses thesis policy implications.

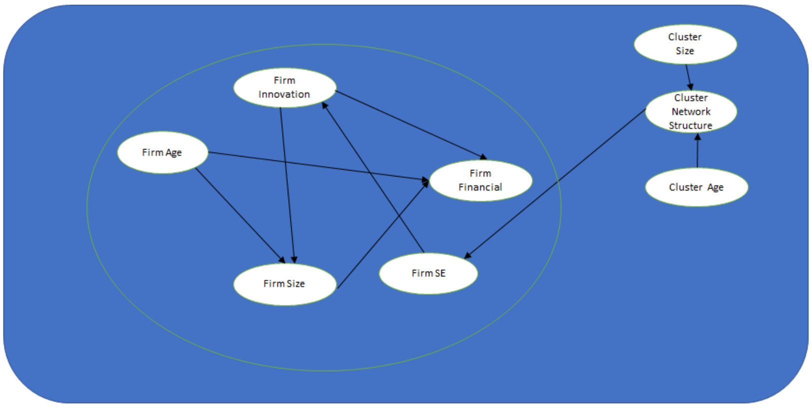

Figure 8.1 Business Cluster Success Factors (Summary)

8.2 Policy Implications

Historically, many tries were put together, claiming that they align the needed policies for any business cluster to sustain, starting from Silicon Valley imitation theories, which try to build a similar cluster structure as the one found in Silicon Valley. Triple-helix builds on the connection of academia, public (government), and industry [see (Etzkowitz and Leydesdorff, 2000; Klofsten et al., 1999; Leydesdorff and Etzkowitz, 2003)]. This hypothesis builds on the fact that business clusters are innovation factory, and innovation builds on knowledge spillover between cluster firms and university research, which assumes that most innovation comes from knowledge which is produced through universities researches.

Moreover, it assumes that government support is crucial in enhancing the cluster development by providing the needed infrastructures (such as fast broadband, traffic, housing, and many others [see (Skokan et al., 2012; Grilli and Murtinu, 2014)]. Government support is another matrix which assumed to help stimulating firms' development inside the business cluster and help entrepreneurial in building their own businesses (De Fontenay, 2004). This leads into building cluster structure, generally in form of science parks, near a university, and further enhanced by Cluster Initiatives (CIs), which are responsible for building and monitoring the development of business clusters.

The thesis results suggests that policymakers should pay attention into a number of factors that helps business cluster to produce more innovations. First of all, they should select the right networking structure especially at early stages of cluster development which minimise knowledge aquasation cost, then select the right qualified personnel to run the CI organisation, who is capable of evaluating incoming innovation projects. Moreover, a well-stablished training programmes for new firms manager should be put inplace to help new managers evaluate innovation project, so project evaluation can eventually move from CI managers to firms managers. After that, they should facilitate social events and encourage firms networking between inhabited firms. They also should help firms to obtain the right investment for both networking and growing and connect firms with VCs. Emparical results prove the importance of firms age and cluster age, therfore, business policymakers should put the right strategies to reduce the cluster and firms age impact and prevent it from getting into a lock-in stage, by encouraging new innovation, new knowledge and new firms formation.

On the other hand, empirical study part of this thesis (Chapter 4: and Chapter 5:) show the need for building a comprehensive evaluation mechanism, which takes into account business cluster success indicators as a starting point of any policy changes. Thus, Figure 8.2 summarises the proposed evaluation mechanism, which is further explained in the next paragraphs.

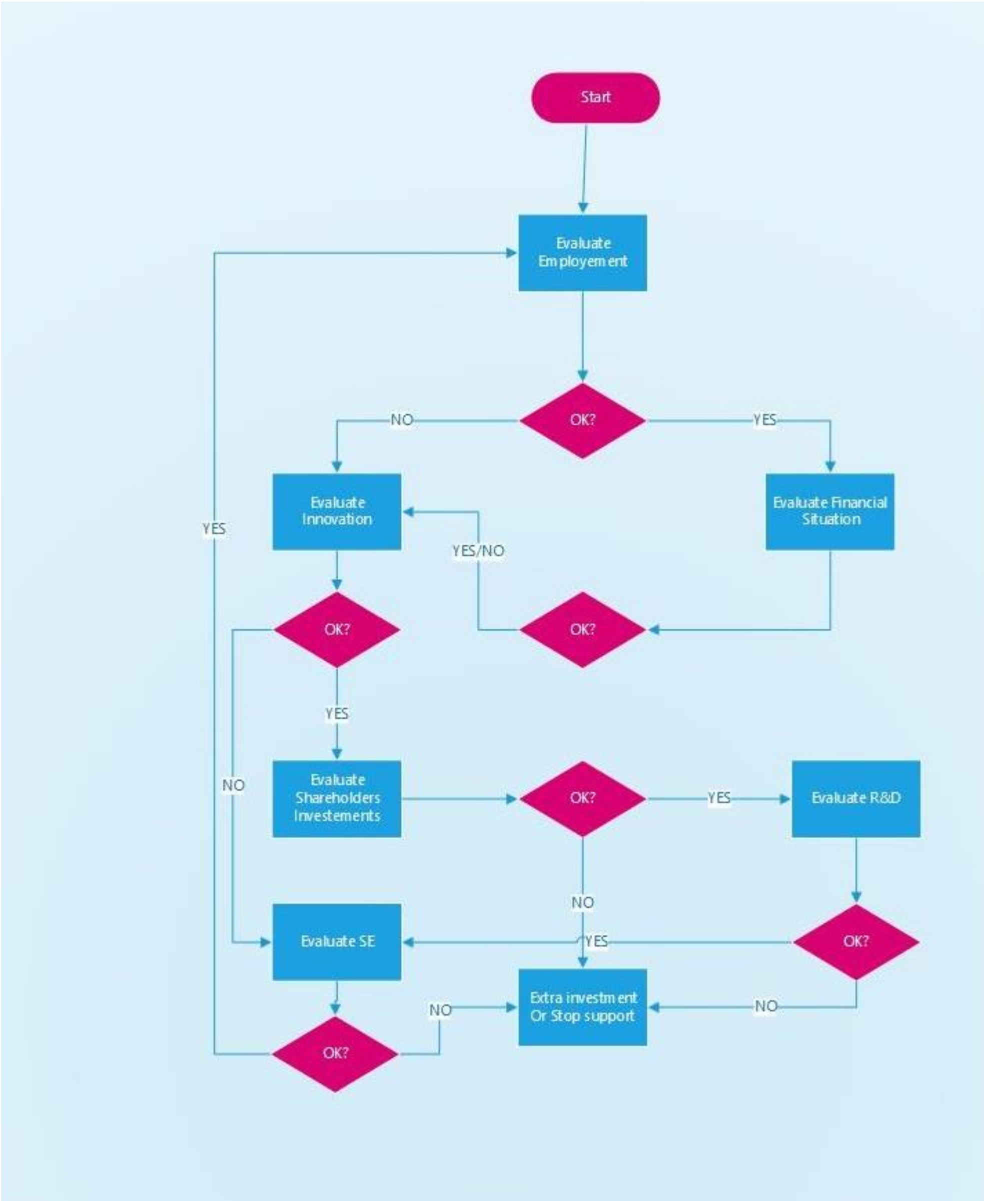

Figure 8.2 Business Cluster Evaluation Mechanism (Summary)

The process must start at the micro-level, by evaluating firms' output. It would start by evaluating the firms' employment, then financial situation and finally, firm innovation capabilities. As described in figure 8.2, the process will follow the following steps:

1. Evaluate firms' employment, if it is good, then you move into steps 2, otherwise, you go to steps 4, and 5.
2. Evaluate firm innovation capabilities, if it is good then, you move into step 4, otherwise, we go to step 3.
3. If a problem is found in the innovation capabilities, then we check the social expenses, and if a firm is lacking good social expenses investment, we move to step 4, otherwise, we apply step 5.
4. In this step, an investment evaluation is needed, to check if a firm really needs more investment or lack more of it is an internal organisation (firms' specific effect).
5. Now, if innovation was reporting good values, then we check if a firm needs more shareholders contribution, if it is ok, then we check if it needs more investment from its shareholders or investment bodies by applying step 4.
6. If no more shareholders' investment is needed, there might be a need for more R&D investment, if this is the case, then we move to step 4. Otherwise, we move to step 1 for the next firm until there is no firm which needs evaluation, then we move to step 7.
7. Now, they move into evaluating the cluster development at the aggregate level, first by evaluating the total number of firms corresponding to the cluster age, if they are good, then they evaluate the number of employees to the corresponding number of firms. If they are okay, we move to step 8, otherwise, they execute step 10.
8. We evaluate the total turnover of all the firms, if it is okay, we move to step 9, otherwise move to step 10.
9. Finally, they evaluate the total produced innovation corresponding to the total social expenses, if it is fine, then they stop at this stage, otherwise, they move to step 11.
10. In this stage, a closer look into the number of produced firms must be done. If they need to graduate more firms into the cluster or not. This would help to improve the overall cluster financial and employability status. Of course, after controlling for cluster capacity.

11. If innovation is not performing well at the aggregate level, they must evaluate if the amount of socializing is well aligned with the number of employees available on-cluster and evaluate if they need to increase the number of social investments and facilitate more networking events (activities).

This would enable firms' managers and cluster managers' to systematically evaluate the progress of its firms and cluster and identify their problems and strengths. This shapes how to plan its investments and identify future approaches. These are all based on the extracted models in chapters 5, 6, and 7. However, we believe the innovative clusters would start by discussing the networking model and how knowledge flows between its inhabitants. Then, run a regular evaluation model based on the above. Of course, this is not a static model and might need adaptation based on the cluster needs and (perhaps) budget.

In conclusion, we believe that cluster managers (at least) must run a regular evaluation of its own and inhabitants' performance. However, the model presented in this section set the major areas, which the cluster must evaluate, and the relative steps to follow.

8.3 Future Research

This work shed light for further research questions, and it has several research implications and extensions involved in this research. This section discusses both, research implications and extensions.

We believe that this research set foundations for further research on this field, and it can be extended in many directions. First of all, more use cases can be considered to verify if what is identified as success factors in this research are portable to other cases. thus, future studies should consider younger clusters and the pattern of development inside young clusters. In this sense, multi-cultural, multi-national (cross borders) cases must be considered. In that respect, more factors must be considered, for example, the availability of similar industrial cluster, and the distance factor (between clusters). Cluster available spaces as well as size, initial investment (for both firms and CIs), networking factor by analysing the firms as well as the cluster networking structures and how this is mapped with social expenses and firms' innovation, and financial productivity using, e.g. the pattern of cluster networking structure.

Moreover, the internal CIs structure and establishment vision is a very important factor to consider. Product innovation, as well as organisational innovation, is a further matrix which must be taken into account, where organisational innovation is input into other innovation output, e.g patents or products. On the other hand, it is vital to study the cases of failed business clusters and the reasons behind that failure as well as which success factors were missing that led business clusters to faile.

Furthermore, it is crucial to identify the best method for measuring a group of firms' efficiencies, as we observed different results if we average against the number of employees or number of firms. Moreover, studying the nature of firms (product and research-oriented, or consultancy) on- and off-cluster will help firms to identify the most suitable place to locate. Furthermore, adding more indicators such as the available space on-cluster and comparing rents on- and off-cluster will help researchers and policymakers understanding the pattern of firms' location. Furthermore, using big data, machine learning as well as exploring at micro-level (firms' level) in evaluating different case studies and build a predictive model (e.g. 3D landscape model, as in Mellor, 2018) will help policymakers identifying the current development stage of a business cluster and how to improve it. Moreover, a comprehensive study of the spillover effect between on- and off-cluster firms is needed, which will help to identify the best strategy for regional authorities. For example, if the regional developers need to keep the two groups of firms isolated, or perhaps moves them together especially if they are working in the same industries (similar to the case being discussed here). One approach would be to analyse the connections (formal and informal) between firms located on- and off-cluster, and the financial, innovation and knowledge spillover impact using, e.g. isolated firms as a control group, and having more cases will help validate this work.

Moreover, considering a hybrid methodological approach will further verify the thesis outcome by adding a subjective dimension into the study. This can be achieved by analysing experts thought on what the business clusters' success factors are, and if these are consistent with the data analysis outcome.

In summary, although this research adds to the current understanding of business clusters' success, it opens the doors for further questions and analysis.

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Appendix 1 Sample Econometrics Models

This appendix aims at explore a sample of the different models we tried to build. However, if problems with regression to the mean are encountered, then "Instrumental Variables" may be used to check for endogeneity, (e.g. turnover versus employees, which are obviously linked).

Appendix 1A: Data Definition

This appendix defines all data points presented in Appendix 1B. This is represented in Table 0.1.

Table 0.1 Data Definitions

Data point	Definition
Ln_emps	Natural logorathmic of number of employees
FirmsAge	Age of the firm since establishment
Ln_turnover	Natural logarithmic of the turnover
Ln_P_L	Natural logarithmic of patents and licenses
P_L_TO_Turnover	Patents and licenses ratio to turnover
Ln_R_D	Natural logarithmic of R&D
Ln_S_E	Natural logarithmic of social expenditures
Totalcurrentinvestments	Total Firms' investment
Achievedshareholdercontribution	Total shareholders contribution (investment)
Receivablesfromgroupassociate	Total receivables (from firms' own group) as part of the group profit
SharesInGroupAssociate	Total shares values in other parts of firms' group
PatentsandLicense	Book value of patents and licenses
CapitalisedR&DExpediture	R&D investement
GroupContributions	Company's contribution to one or more of its sister companies

Econometric Models for $ln(emp_{i,t})$

Appendix 1B: Econometric Models

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.0966944	.0158485	6.10	0.000	.0655475	.1278413
c.FirmsAge#c.FirmsAge	-.0024467	.0005796	-4.22	0.000	-.0035857	-.0013077
ln_turnover	.065917	.0139819	4.71	0.000	.0384386	.0933954
ln_P_L	-.0113678	.0171924	-0.66	0.509	-.0451558	.0224203
_cons	.7050626	.1396775	5.05	0.000	.4305564	.9795687
sigma_u	.99690523					
sigma_e	.41861245					
rho	.85010443	(fraction of variance due to u_i)				

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.100098	.0198104	5.05	0.000	.0611446	.1390514
c.FirmsAge#c.FirmsAge	-.0025273	.0006961	-3.63	0.000	-.0038961	-.0011585
ln_turnover	.0542977	.0160044	3.39	0.001	.022828	.0857674
ln_P_L						
L1.	-.0183911	.0185213	-0.99	0.321	-.0548097	.0180275
_cons	.7930368	.1736077	4.57	0.000	.4516702	1.134403
sigma_u	1.0688772					
sigma_e	.4130538					
rho	.87006937	(fraction of variance due to u_i)				

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.1067536	.0207178	5.15	0.000	.0660042	.1475031
c.FirmsAge#c.FirmsAge	-.0026019	.00073	-3.56	0.000	-.0040377	-.0011661
ln_turnover	.0634144	.0206192	3.08	0.002	.0228589	.1039699
P_L_TO_Turnover						
L1.	.0113029	.005679	1.99	0.047	.000133	.0224727
_cons	.7281952	.2015041	3.61	0.000	.3318601	1.12453
sigma_u	1.0418424					
sigma_e	.40997301					
rho	.86591459	(fraction of variance due to u_i)				

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.1063215	.0208298	5.10	0.000	.0653513	.1472916
c.FirmsAge#c.FirmsAge	-.0025986	.0007311	-3.55	0.000	-.0040367	-.0011605
ln_turnover	.0629586	.0207408	3.04	0.003	.0221634	.1037538
P_L_TO_Turnover						
L1.	.01132	.0056873	1.99	0.047	.0001337	.0225063
ln_R_D	.0032527	.0140187	0.23	0.817	-.0243207	.0308262
_cons	.7318108	.2023825	3.62	0.000	.3337437	1.129878
sigma_u	1.0397685					
sigma_e	.41053798					
rho	.86513015	(fraction of variance due to u_i)				

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.1063918	.0207205	5.13	0.000	.0656365	.147147
c.FirmsAge#c.FirmsAge	-.00265	.0007316	-3.62	0.000	-.0040889	-.0012111
ln_turnover	.0607729	.0207852	2.92	0.004	.0198903	.1016554
P_L_TO_Turnover						
L1.	.0114468	.0056807	2.02	0.045	.0002735	.0226201
ln_R_D						
L1.	.0128091	.0127291	1.01	0.315	-.0122279	.037846
_cons	.7466696	.202335	3.69	0.000	.348696	1.144643

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.0690199	.0198843	3.47	0.001	.0299094	.1081305
c.FirmsAge#c.FirmsAge	-.0016978	.0006884	-2.47	0.014	-.0030519	-.0003437
ln_turnover	.02416	.0198484	1.22	0.224	-.01488	.0631999
P_L_TO_Turnover						
L1.	.0108982	.0052729	2.07	0.039	.000527	.0212694
ln_S_E						
L1.	.1421668	.0189856	7.49	0.000	.1048239	.1795098
_cons	.4550831	.1906064	2.39	0.018	.0801786	.8299877

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.1067536	.0207178	5.15	0.000	.0660042	.1475031
c.FirmsAge#c.FirmsAge	-.0026019	.00073	-3.56	0.000	-.0040377	-.0011661
ln_turnover	.0634144	.0206192	3.08	0.002	.0228589	.1039699
P_L_TO_Turnover						
L1.	.0113029	.005679	1.99	0.047	.000133	.0224727
_cons	.7281952	.2015041	3.61	0.000	.3318601	1.12453

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.1070491	.0208116	5.14	0.000	.0661148	.1479835
c.FirmsAge#c.FirmsAge	-.0026072	.0007316	-3.56	0.000	-.0040462	-.0011682
ln_turnover	.063209	.0206796	3.06	0.002	.0225341	.1038838
P_L_TO_Turnover						
L1.	.0113153	.0056874	1.99	0.047	.0001287	.0225018
Totalcurrentinvestments						
L1.	-8.10e-07	4.49e-06	-0.18	0.857	-9.64e-06	8.02e-06
_cons	.728608	.201801	3.61	0.000	.3316847	1.125531
sigma_u	1.041622					
sigma_e	.41055074					
rho	.86553801	(fraction of variance due to u_i)				

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.1049392	.02064	5.08	0.000	.0643423	.1455362
c.FirmsAge#c.FirmsAge	-.0024819	.0007289	-3.40	0.001	-.0039156	-.0010482
ln_turnover	.063818	.020524	3.11	0.002	.0234494	.1041867
P_L_TO_Turnover						
L1.	.0112345	.0056526	1.99	0.048	.0001165	.0223526
AchievedShareholdercontributions	.0000889	.0000432	2.06	0.040	3.88e-06	.0001739
_cons	.7174788	.2006322	3.58	0.000	.3228544	1.112103
sigma_u	1.039164					
sigma_e	.40806147					
rho	.86640133	(fraction of variance due to u_i)				

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.1088427	.0205985	5.28	0.000	.0683273	.149358
c.FirmsAge#c.FirmsAge	-.0026368	.0007253	-3.64	0.000	-.0040634	-.0012103
ln_turnover	.0586878	.0205784	2.85	0.005	.018212	.0991635
P_L_TO_Turnover						
L1.	.0115705	.0056423	2.05	0.041	.0004728	.0226683
AchievedShareholdercontributions						
L1.	.0000638	.0000269	2.37	0.018	.0000109	.0001166
_cons	.7451076	.2002882	3.72	0.000	.3511599	1.139055
sigma_u	1.0536877					
sigma_e	.40724124					
rho	.87003761	(fraction of variance due to u_i)				

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.1077576	.0206466	5.22	0.000	.0671473	.1483679
c.FirmsAge#c.FirmsAge	-.0026356	.0007256	-3.63	0.000	-.0040628	-.0012085
ln_turnover	.0591688	.0205946	2.87	0.004	.0186607	.0996769
P_L_TO_Turnover						
L1.	.0112538	.0056569	1.99	0.047	.0001271	.0223805
AchievedShareholdercontributions						
L1.	.0000633	.0000269	2.35	0.019	.0000104	.0001162
Profit						
L1.	-9.64e-07	1.14e-06	-0.85	0.397	-3.20e-06	1.27e-06
_cons	.7564548	.2008158	3.77	0.000	.3614652	1.151444

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.1089568	.0206402	5.28	0.000	.0683591	.1495544
c.FirmsAge#c.FirmsAge	-.0026407	.0007267	-3.63	0.000	-.0040701	-.0012113
ln_turnover	.0585959	.0206157	2.84	0.005	.0180464	.0991454
P_L_TO_Turnover						
L1.	.0115763	.0056504	2.05	0.041	.0004624	.0226902
AchievedShareholdercontributions						
L1.	.0000638	.0000269	2.37	0.018	.0000109	.0001167
ReceivablesfromGroupAssociates						
L1.	1.95e-07	1.22e-06	0.16	0.873	-2.20e-06	2.59e-06
_cons	.7443006	.2006366	3.71	0.000	.3496635	1.138938

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.1098913	.0209988	5.23	0.000	.0685877	.1511948
c.FirmsAge#c.FirmsAge	-.0026782	.0007428	-3.61	0.000	-.0041392	-.0012172
ln_turnover	.0585014	.0206474	2.83	0.005	.0178891	.0991137
P_L_TO_Turnover						
L1.	.0115604	.0056585	2.04	0.042	.0004305	.0226904
AchievedShareholdercontributions						
L1.	.0000638	.0000269	2.37	0.018	.0000108	.0001169
ReceivablesfromGroupAssociates						
L1.	1.36e-07	1.24e-06	0.11	0.913	-2.31e-06	2.58e-06
SharesinGroupAssociates	-4.30e-07	1.71e-06	-0.25	0.801	-3.79e-06	2.93e-06
_cons	.7431621	.2009628	3.70	0.000	.3478794	1.138445

ln_emps	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FirmsAge	.1098914	.0209685	5.24	0.000	.068648	.1511348
c.FirmsAge#c.FirmsAge	-.0026786	.0007417	-3.61	0.000	-.0041375	-.0012198
ln_turnover	.0585553	.0206117	2.84	0.005	.0180138	.0990969
P_L_TO_Turnover						
L1.	.0115553	.0056501	2.05	0.042	.0004419	.0226687
AchievedShareholdercontributions						
L1.	.0000638	.0000269	2.37	0.018	.0000109	.0001168
SharesinGroupAssociates	-4.65e-07	1.67e-06	-0.28	0.781	-3.76e-06	2.83e-06
_cons	.7436105	.2006305	3.71	0.000	.3489854	1.138236

Econometrics Models for $n(Turnover_{i,t})$

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Numberofemployees	.0518954	.0108235	4.79	0.000	.0306045	.0731863
c.Numberofemployees#						
c.Numberofemployees	-.0002046	.0000501	-4.08	0.000	-.0003031	-.000106
FirmsAge	.0870023	.0404869	2.15	0.032	.0073608	.1666439
c.FirmsAge#c.FirmsAge	-.0027146	.0013896	-1.95	0.052	-.005448	.0000189
P_L_TO_Turnover						
L1.	.0256484	.010538	2.43	0.015	.0049193	.0463776
--.	-.1181951	.0346659	-3.41	0.001	-.1863861	-.0500042
ln_R_D						
L1.	.0552627	.0234603	2.36	0.019	.0091142	.1014112
_cons	7.415426	.2569206	28.86	0.000	6.910039	7.920812

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Numberofemployees	.1271823	.0142075	8.95	0.000	.0992972	.1550673
c.Numberofemployees#						
c.Numberofemployees	-.0007749	.0001135	-6.83	0.000	-.0009976	-.0005522
FirmsAge	-.0513619	.024745	-2.08	0.038	-.0999287	-.002795
c.FirmsAge#c.FirmsAge	.0012536	.0008885	1.41	0.159	-.0004902	.0029973
P_L_TO_Turnover						
L1.	-.7576113	3.491459	-0.22	0.828	-7.610278	6.095055
--.	1.413853	4.043727	0.35	0.727	-6.522747	9.350453
_cons	7.000189	.1521848	46.00	0.000	6.701497	7.298882

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Numberofemployees	.2687951	.0167403	16.06	0.000	.2359535	.3016366
c.Numberofemployees#						
c.Numberofemployees	-.0017534	.0001473	-11.90	0.000	-.0020424	-.0014643
FirmsAge	-.028499	.0298939	-0.95	0.341	-.0871455	.0301476
c.FirmsAge#c.FirmsAge	-.0005282	.0011137	-0.47	0.635	-.0027132	.0016567
_cons	5.799736	.163431	35.49	0.000	5.479114	6.120359

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Numberofemployees	.1414347	.0133316	10.61	0.000	.115277	.1675924
c.Numberofemployees# c.Numberofemployees	-.0008685	.0001066	-8.14	0.000	-.0010778	-.0006593
FirmsAge	-.0055119	.0201899	-0.27	0.785	-.0451261	.0341023
c.FirmsAge#c.FirmsAge	-.0005771	.0007588	-0.76	0.447	-.0020659	.0009118
P_L_TO_Turnover	-.3937314	.4090463	-0.96	0.336	-1.196314	.4088512
_cons	6.655454	.1108338	60.05	0.000	6.437989	6.87292

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Numberofemployees	.1612796	.0200288	8.05	0.000	.121971	.2005883
c.Numberofemployees# c.Numberofemployees	-.0010253	.0001601	-6.40	0.000	-.0013395	-.000711
FirmsAge	-.1236215	.0341872	-3.62	0.000	-.1907177	-.0565253
c.FirmsAge#c.FirmsAge	.0025667	.0012234	2.10	0.036	.0001657	.0049676
P_L_TO_Turnover L1.	-2.650294	3.680129	-0.72	0.472	-9.87295	4.572361
_cons	7.192389	.2084354	34.51	0.000	6.783311	7.601466

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Numberofemployees	.2687656	.0167351	16.06	0.000	.2359343	.3015969
c.Numberofemployees# c.Numberofemployees	-.0017545	.0001473	-11.92	0.000	-.0020434	-.0014656
FirmsAge	-.0405468	.0157547	-2.57	0.010	-.0714547	-.0096389
_cons	5.835414	.1450456	40.23	0.000	5.55086	6.119967

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Numberofemployees	.2567594	.0186511	13.77	0.000	.2201603	.2933586
c.Numberofemployees# c.Numberofemployees	-.0016978	.0001607	-10.56	0.000	-.0020132	-.0013824
FirmsAge	-.0446254	.018061	-2.47	0.014	-.0800667	-.0091842
PatentsandLicenses L1.	.0001054	.0000497	2.12	0.034	7.98e-06	.0002029
CapitalizedRDExpenditure L1.	.0000282	.0000408	0.69	0.490	-.0000519	.0001083
_cons	5.958591	.1863253	31.98	0.000	5.592963	6.324219

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Numberofemployees	.2560417	.0186314	13.74	0.000	.2194813	.2926022
c.Numberofemployees# c.Numberofemployees	-.0016945	.0001606	-10.55	0.000	-.0020096	-.0013793
FirmsAge	-.0434433	.017984	-2.42	0.016	-.0787335	-.0081531
PatentsandLicenses L1.	.0001135	.0000519	2.19	0.029	.0000118	.0002153
AchievedShareholdercontributions	9.26e-06	.0000181	0.51	0.608	-.0000262	.0000447
_cons	5.952074	.1863566	31.94	0.000	5.586385	6.317763

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Numberofemployees	.2578091	.0186757	13.80	0.000	.2211617	.2944566
c.Numberofemployees# c.Numberofemployees	-.0016881	.0001605	-10.51	0.000	-.0020031	-.001373
FirmsAge	-.0452467	.0180388	-2.51	0.012	-.0806443	-.0098491
PatentsandLicenses L1.	.0000991	.00005	1.98	0.048	1.08e-06	.0001972
AchievedShareholdercontributions L1.	-.0000257	.000022	-1.17	0.242	-.0000688	.0000174
_cons	5.973716	.1868564	31.97	0.000	5.607046	6.340386

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Numberofemployees	.2507245	.0190484	13.16	0.000	.2133457	.2881034
c.Numberofemployees# c.Numberofemployees	-.001652	.0001633	-10.11	0.000	-.0019725	-.0013315
FirmsAge	-.0437016	.0179713	-2.43	0.015	-.0789669	-.0084364
PatentsandLicenses L1.	.0001198	.0000507	2.36	0.018	.0000203	.0002193
Groupcontributions L1.	.000038	.0000283	1.34	0.181	-.0000176	.0000935
_cons	5.974881	.186723	32.00	0.000	5.608472	6.341289

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Numberofemployees	.132549	.0145029	9.14	0.000	.1040857	.1610124
c.Numberofemployees# c.Numberofemployees	-.0008132	.0001159	-7.01	0.000	-.0010407	-.0005857
FirmsAge	-.0195867	.0116597	-1.68	0.093	-.04247	.0032966
PatentsandLicenses L1.	.0000105	.0000365	0.29	0.774	-.0000612	.0000822
R_D_TO_Turnover	-.0077766	.0754644	-0.10	0.918	-.1558832	.1403299
_cons	6.784584	.1250914	54.24	0.000	6.53908	7.030089

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Numberofemployees	.1261626	.0141972	8.89	0.000	.0982979	.1540273
c.Numberofemployees# c.Numberofemployees	-.000766	.0001134	-6.76	0.000	-.0009886	-.0005435
FirmsAge	-.0205676	.0116667	-1.76	0.078	-.0434657	.0023306
P_L_TO_Turnover L1.	-.6596283	3.492753	-0.19	0.850	-7.514824	6.195567
--.	1.318596	4.045462	0.33	0.745	-6.621397	9.258589
_cons	6.886481	.1291672	53.31	0.000	6.632965	7.139996

ln_turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Numberofemployees	.1598326	.0200388	7.98	0.000	.1205043	.1991609
c.Numberofemployees# c.Numberofemployees	-.0010117	.0001602	-6.32	0.000	-.001326	-.0006973
FirmsAge	-.0608417	.0162363	-3.75	0.000	-.0927073	-.0289761
P_L_TO_Turnover L1.	-2.342917	3.682115	-0.64	0.525	-9.56947	4.883636
R_D_TO_Turnover L1.	.149691	.1077427	1.39	0.165	-.0617657	.3611477
_cons	6.955792	.1763834	39.44	0.000	6.60962	7.301964

Econometrics Models for $Innov_{i,t}$

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
S_E_TO_Turnover	.5468034	.0507847	10.77	0.000	.4469768	.64663
_cons	.088191	.1535746	0.57	0.566	-.213688	.39007
sigma_u	1.1867597					
sigma_e	3.3665577					
rho	.11053103	(fraction of variance due to u_i)				

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
S_E_TO_Turnover	3.697668	.1245953	29.68	0.000	3.452749	3.942586
c.S_E_TO_Turnover# c.S_E_TO_Turnover	-.0530164	.0020293	-26.13	0.000	-.0570055	-.0490273
R_D_TO_Turnover	-.549995	.5042686	-1.09	0.276	-1.541241	.4412511
_cons	-.5273826	.1047423	-5.04	0.000	-.7332755	-.3214896

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
S_E_TO_Turnover	3.698027	.1247473	29.64	0.000	3.452809	3.943246
c.S_E_TO_Turnover# c.S_E_TO_Turnover	-.053022	.0020318	-26.10	0.000	-.057016	-.0490281
R_D_TO_Turnover	-.2724891	1.288199	-0.21	0.833	-2.804733	2.259755
c.R_D_TO_Turnover# c.R_D_TO_Turnover	-.1243021	.530861	-0.23	0.815	-1.167829	.9192245
_cons	-.5384574	.1150352	-4.68	0.000	-.7645849	-.3123298

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
S_E_TO_Turnover	3.693339	.1248963	29.57	0.000	3.447829	3.938849
c.S_E_TO_Turnover# c.S_E_TO_Turnover	-.0529467	.0020323	-26.05	0.000	-.0569416	-.0489519
Numberofemployees	-.0003862	.0111657	-0.03	0.972	-.0223347	.0215623
_cons	-.5619868	.2012967	-2.79	0.005	-.9576779	-.1662958

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
S_E_TO_Turnover	.1325112	.1479921	0.90	0.371	-.1585691	.4235915
c.S_E_TO_Turnover# c.S_E_TO_Turnover	.0461506	.0037497	12.31	0.000	.0387754	.0535259
FirmsAge	.1522102	.0614113	2.48	0.014	.0314225	.2729978
c.FirmsAge#c.FirmsAge	-.0043638	.0021673	-2.01	0.045	-.0086265	-.000101
AchievedShareholdercontributions L1.	7.76e-06	.0000811	0.10	0.924	-.0001518	.0001673
_cons	-.8689348	.4103446	-2.12	0.035	-1.676027	-.0618429

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
S_E_TO_Turnover	.1402009	.1485943	0.94	0.346	-.1520609	.4324627
c.S_E_TO_Turnover# c.S_E_TO_Turnover	.0459169	.0037645	12.20	0.000	.0385128	.053321
FirmsAge	.0421215	.0280859	1.50	0.135	-.0131191	.0973621
AchievedShareholdercontributions L1.	6.14e-06	.0000815	0.08	0.940	-.0001541	.0001664
_cons	-.3921991	.3366206	-1.17	0.245	-1.054279	.2698812
sigma_u	1.0500766					
sigma_e	1.2402599					
rho	.41753137	(fraction of variance due to u_i)				

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
S_E_TO_Turnover	.1325571	.1482115	0.89	0.372	-.1589578	.4240721
c.S_E_TO_Turnover# c.S_E_TO_Turnover	.0461494	.0037553	12.29	0.000	.0387632	.0535357
FirmsAge	.152278	.0615257	2.48	0.014	.0312641	.2732918
c.FirmsAge#c.FirmsAge	-.0043695	.0021756	-2.01	0.045	-.0086487	-.0000903
AchievedShareholdercontributions L1.	7.75e-06	.0000812	0.10	0.924	-.000152	.0001675
Groupcontributions L1.	1.97e-06	.0000512	0.04	0.969	-.0000988	.0001027
_cons	-.8686364	.4110131	-2.11	0.035	-1.677052	-.0602213

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
S_E_TO_Turnover	.140054	.1488145	0.94	0.347	-.152644	.4327519
c.S_E_TO_Turnover# c.S_E_TO_Turnover	.0459209	.0037701	12.18	0.000	.0385057	.0533361
FirmsAge	.0423259	.0281998	1.50	0.134	-.0131393	.0977911
AchievedShareholdercontributions L1.	6.17e-06	.0000816	0.08	0.940	-.0001543	.0001666
Groupcontributions L1.	-5.15e-06	.0000513	-0.10	0.920	-.0001061	.0000958
_cons	-.394634	.3379752	-1.17	0.244	-1.059385	.2701172
sigma_u	1.0504373					
sigma_e	1.242038					
rho	.41700167	(fraction of variance due to u_i)				

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
S_E_TO_Turnover	.1402009	.1485943	0.94	0.346	-.1520609	.4324627
c.S_E_TO_Turnover# c.S_E_TO_Turnover	.0459169	.0037645	12.20	0.000	.0385128	.053321
FirmsAge	.0421215	.0280859	1.50	0.135	-.0131191	.0973621
AchievedShareholdercontributions L1.	6.14e-06	.0000815	0.08	0.940	-.0001541	.0001664
_cons	-.3921991	.3366206	-1.17	0.245	-1.054279	.2698812

ln_P_L	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Socialexpenses	-.0000119	.0000272	-0.44	0.663	-.0000654	.0000416
_cons	.5706132	.0954965	5.98	0.000	.3829388	.7582876
sigma_u	1.3317267					
sigma_e	1.1508645					
rho	.57246757	(fraction of variance due to u_i)				

ln_P_L	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Socialexpenses						
L1.	-.0000371	.0000333	-1.11	0.266	-.0001025	.0000283
_cons	.6710994	.1128463	5.95	0.000	.4492143	.8929845
sigma_u	1.4697768					
sigma_e	1.1759854					
rho	.60968973	(fraction of variance due to u_i)				

ln_P_L	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Socialexpenses						
L1.	-.000124	.0000659	-1.88	0.061	-.0002537	5.61e-06
cL.Socialexpenses#						
cL.Socialexpenses	2.18e-09	1.43e-09	1.53	0.128	-6.28e-10	4.99e-09
_cons	.8309908	.1538132	5.40	0.000	.5285515	1.13343

ln_P_L	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Socialexpenses						
L1.	.0000175	.0000815	0.21	0.830	-.0001428	.0001779
cL.Socialexpenses#						
cL.Socialexpenses	3.16e-10	1.55e-09	0.20	0.839	-2.74e-09	3.37e-09
CapitalizedRDExpenditure	-.0000452	.0000156	-2.90	0.004	-.0000759	-.0000145
_cons	.5770008	.1757362	3.28	0.001	.2314518	.9225497

ln_P_L	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Socialexpenses						
L1.	-4.93e-06	.0000396	-0.12	0.901	-.0000828	.000073
CapitalizedRDExpenditure						
L1.	-.0000214	.0000144	-1.49	0.137	-.0000497	6.87e-06
_cons	.6073665	.1205248	5.04	0.000	.3703814	.8443516

ln_P_L	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Socialexpenses						
L1.	-.0000304	.0000415	-0.73	0.465	-.000112	.0000512
CapitalizedRDExpenditure						
L1.	-.0000209	.0000143	-1.46	0.146	-.0000491	7.31e-06
FirmsAge	.0536691	.0271285	1.98	0.049	.0003265	.1070117
_cons	.0520575	.3052952	0.17	0.865	-.5482423	.6523573

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Socialexpenses						
L1.	.0001467	.0001479	0.99	0.322	-.0001443	.0004377
FirmsAge	-.0885692	.100374	-0.88	0.378	-.2859872	.1088488
CapitalizedRDExpenditure						
L1.	-.0000244	.0000507	-0.48	0.630	-.0001242	.0000753
_cons	.9651148	1.125258	0.86	0.392	-1.248069	3.178299

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Socialexpenses	.0001111	.0001185	0.94	0.349	-.0001217	.000344
FirmsAge	-.0421837	.076548	-0.55	0.582	-.1926548	.1082875
CapitalizedRDExpenditure	-.0000252	.0000429	-0.59	0.557	-.0001096	.0000591
_cons	.4702729	.8068654	0.58	0.560	-1.115791	2.056337

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
S_E_TO_Turnover	.5505286	.0511142	10.77	0.000	.4500529	.6510043
FirmsAge	.0468962	.0633897	0.74	0.460	-.0777096	.171502
R_D_TO_Turnover	-.1832986	.8239205	-0.22	0.824	-1.802888	1.436291
_cons	-.415526	.712867	-0.58	0.560	-1.816816	.9857642

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
S_E_TO_Turnover						
L1.	-.110902	.0318315	-3.48	0.001	-.1735147	-.0482893
FirmsAge	.0390394	.0271316	1.44	0.151	-.0143286	.0924074
R_D_TO_Turnover						
L1.	-.0405407	.3021601	-0.13	0.893	-.6348917	.5538104
_cons	-.3096916	.3244715	-0.95	0.341	-.9479295	.3285463

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
S_E_TO_Turnover						
L1.	.2268284	.1412994	1.61	0.109	-.0511115	.5047683
cL.S_E_TO_Turnover#						
cL.S_E_TO_Turnover	-.0087602	.0035723	-2.45	0.015	-.0157869	-.0017334
FirmsAge	.0318355	.0270923	1.18	0.241	-.0214559	.0851268
R_D_TO_Turnover						
L1.	-.0812499	.3004027	-0.27	0.787	-.6721505	.5096507
_cons	-.2881293	.3222115	-0.89	0.372	-.9219284	.3456698

P_L_TO_Turnover	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
S_E_TO_Turnover						
L1.	.2420042	.1403418	1.72	0.086	-.0340491	.5180574
cL.S_E_TO_Turnover#						
cL.S_E_TO_Turnover	-.0091781	.0035455	-2.59	0.010	-.0161522	-.002204
Groupcontributions						
L1.	3.75e-07	.0000481	0.01	0.994	-.0000943	.000095
_cons	.0786059	.0645489	1.22	0.224	-.0483623	.2055741