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General Purpose Technologies from a Knowledge Perspective – A Computational Social Science Approach to Innovation Networks in Nanotechnology

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Student Number: 09167081

The thesis is submitted to University College Dublin in fulfilment of the requirements for the degree of Doctor of Philosophy in Complex Systems and Computational Social Science

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September 2016
Preface

This dissertation is based on the research I conducted at University College Dublin as a full time PhD student (2010-2013) and as an off-campus part time PhD student at the EA European Academy of Technology and Innovation Assessment (2013-2016). During my time at UCD, I was supported financially by the European Commission’s FP6 Marie-Curie Initial Training Network Project “ManETEI” – Managing Emerging Technologies for Economic Impact. Within the project I was also given the opportunity to participate in several academic conferences and complete an industrial placement. I am very grateful for having been given this great opportunity.

During the project “ManETEI”, I was lucky to get to know some of the brightest young researchers in Europe. I want to seize this opportunity to thank all of them for the inspirational and motivational talks and discussions we had, for all the shared experiences and problems during the entire project and our respective dissertation projects.

I would also like to thank Prof. Andreas Pyka for making me aware of the open position in Dublin and for bringing me into contact with my then-primary supervisor Prof. Petra Ahrweiler, who offered me the opportunity to earn my doctorate. I am very thankful for her academic advice and support during the entire project and of course for having given me this opportunity in the first place. Another big thank you goes to Diane Payne and her excellent guidance through the PhD process. Also, I want to thank Yuko Conlon for the great off-campus assistance and Prof. Brian Fynes for taking over from Petra Ahrweiler as my primary supervisor.

In course of the research project, I was grateful for the academic discussions, the support I received for getting set up and making life enjoyable in Dublin, and the friends I could make: Marija Drenkovska, Kiril Dichev, Davy van Doren, Bei Gao, Andreas Krüger, Colman McMahon, Michel Schilperoord, Philip Schmadlak and Miriam Wolf. At the EA, my past and current colleagues never fell short of providing support and lending an open ear whenever needed and I am very grateful to having found such an inspiring and pleasant new working environment. Special thanks go to my long-time collaborator Matthias Müller at the University of Hohenheim.

Last but not least, I would like to thank my loved ones: my family and friends for supporting me at all stages in my life, their motivational words and unconditional backing. Finally, my sincerest gratitude and respect goes to Katharina for all her enduring help, unsurpassable encouragement, selfless backup, and the right words at all times. I would not have succeeded in putting together this thesis if it hadn’t been for her. Danke!

Benjamin Schrempf
To Katharina
Table of contents

List of figures .................................................................................................................. VI
Abstract .......................................................................................................................... VIII
Statement of Original Authorship .................................................................................. IX
Collaborations ................................................................................................................ X
1 Introduction .................................................................................................................... 1
  1.1 Research Problem and Relevance ........................................................................... 1
  1.2 Structure of Dissertation ....................................................................................... 4
2 Theoretical Framework ................................................................................................. 6
  2.1 From Neo-classical approaches to the chain-linked model of innovation ............ 6
  2.2 The Neo-Schumpeterian framework .................................................................... 12
  2.3 Complexity and Innovation .................................................................................. 17
  2.4 Innovation in Knowledge Intensive Industries – A Networks Perspective ....... 24
  2.5 The systems of innovation perspective .................................................................. 25
    2.5.1 The Three Main Systems of Innovation Approaches .................................... 27
  2.6 General Purpose Technologies ............................................................................. 43
    2.6.1 The concept of GPTs ..................................................................................... 43
    2.6.2 Literature on GPTs ....................................................................................... 47
3 Design of Research and Methodology ......................................................................... 49
  3.1 Conceptual Framework ........................................................................................... 49
  3.2 Research Questions ............................................................................................... 51
  3.3 Social Network Analysis in Innovation Research .................................................. 53
  3.4 Agent-Based Modelling .......................................................................................... 54
  3.5 The SKIN Model .................................................................................................... 56
    3.5.1 Agents ........................................................................................................... 57
    3.5.2 Knowledge and products .............................................................................. 57
    3.5.3 Markets ......................................................................................................... 59
4 Data ............................................................................................................................... 60
5 Research ......................................................................................................................... 61
  5.1 Publication 1: Nanotechnology in Ireland – an analysis of the patent co-
      classification network .............................................................................................. 61
    5.1.1 Introduction .................................................................................................... 62
    5.1.2 Theoretical Background ............................................................................... 63
    5.1.3 Methods and data ........................................................................................ 66
    5.1.4 Results .......................................................................................................... 68
    5.1.5 Discussion and Conclusion .......................................................................... 71
    5.1.6 References .................................................................................................... 73
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.2</td>
<td>Publication 2: Responsible, Inclusive Innovation and the Nano-divide</td>
<td>80</td>
</tr>
<tr>
<td>5.2.1</td>
<td>Introduction</td>
<td>81</td>
</tr>
<tr>
<td>5.2.2</td>
<td>Innovation, Innovation Systems and Responsible Research and Innovation</td>
<td>82</td>
</tr>
<tr>
<td>5.2.3</td>
<td>The Nano-Divide; Societal Needs, Societal Desirability and Responsiveness</td>
<td>89</td>
</tr>
<tr>
<td>5.2.4</td>
<td>The Nano-Divide, Innovation Systems and Inclusive Innovation</td>
<td>93</td>
</tr>
<tr>
<td>5.2.5</td>
<td>Conclusion</td>
<td>97</td>
</tr>
<tr>
<td>5.2.6</td>
<td>References</td>
<td>99</td>
</tr>
<tr>
<td>5.3</td>
<td>Publication 3: Simulating demand-side effects in innovation</td>
<td>103</td>
</tr>
<tr>
<td>5.3.1</td>
<td>Introduction</td>
<td>105</td>
</tr>
<tr>
<td>5.3.2</td>
<td>Conceptual framework</td>
<td>106</td>
</tr>
<tr>
<td>5.3.3</td>
<td>Key ingredients: knowledge and products</td>
<td>107</td>
</tr>
<tr>
<td>5.3.4</td>
<td>The simulation model</td>
<td>109</td>
</tr>
<tr>
<td>5.3.5</td>
<td>Conclusions and outlook</td>
<td>121</td>
</tr>
<tr>
<td>5.3.6</td>
<td>References</td>
<td>123</td>
</tr>
<tr>
<td>5.4</td>
<td>Publication 4: Modelling the emergence of a general purpose technology</td>
<td>125</td>
</tr>
<tr>
<td>5.4.1</td>
<td>Introduction</td>
<td>127</td>
</tr>
<tr>
<td>5.4.2</td>
<td>General purpose technologies</td>
<td>128</td>
</tr>
<tr>
<td>5.4.3</td>
<td>Modelling GPT networks from a knowledge perspective: Identifying GPTs in SKIN</td>
<td>132</td>
</tr>
<tr>
<td>5.4.4</td>
<td>Further work – indicators and SKIN adaptation</td>
<td>139</td>
</tr>
<tr>
<td>5.4.5</td>
<td>Conclusions</td>
<td>140</td>
</tr>
<tr>
<td>5.4.6</td>
<td>References</td>
<td>142</td>
</tr>
<tr>
<td>6</td>
<td>Discussion of Findings</td>
<td>144</td>
</tr>
<tr>
<td>6.1</td>
<td>Summary and Conclusion</td>
<td>144</td>
</tr>
<tr>
<td>6.2</td>
<td>Limitations and implications</td>
<td>147</td>
</tr>
<tr>
<td>6.3</td>
<td>Further research</td>
<td>153</td>
</tr>
<tr>
<td>7</td>
<td>References</td>
<td>154</td>
</tr>
</tbody>
</table>
List of figures

Fig. 1: Structure of work ................................................................. 5
Fig. 2: Technology push model (1st generation of linear models) ................................ 8
Fig. 3: Market pull model (2nd generation of linear models) ................................ 8
Fig. 4: Chain-linked model ............................................................... 10
Fig. 5: National Systems of Innovation building blocks according to Lundvall (1992) ... 28
Fig. 6: National Systems of Innovation according to Soete (2012) .......................... 29
Fig. 7: The National Systems of Innovation Concept ....................................... 31
Fig. 8: An ideal-type Regional Innovation System ......................................... 34
Fig. 9: Silicon Valley ...................................................................... 36
Fig. 10: Midi-Pyrénées ................................................................. 36
Fig. 11: Steiermark ....................................................................... 37
Fig. 12: Innovation regions of the European Union .......................................... 38
Fig. 13: Sectoral (SSI) and National (NSI) Systems of Innovation ...................... 41
Fig. 14: GPT characteristics ............................................................ 46
Fig. 15: Kene structure in SKIN ...................................................... 58
Fig. 16: Annual and cumulative share of nanotechnology patents, in % ............... 76
Fig. 17: Betweenes centrality distributions ................................................. 77
Fig. 18: Co-classification map of nanotechnology patents in Ireland .................... 77
Fig. 19: All patents co-classification map ................................................. 78
Fig. 20: Detail of figure 16 ................................................................ 79
Fig. 21a and 21b: (a) number of firms (b) average level of compatibility .......... 114
Fig. 22a,b,c,d: histogram of sales measured after 500 ..................................... 116
Fig. 23: QQ-plots for a lognormal distribution (p=0.6) and normal distribution (p=1). 117
Fig. 24: Number of Firms depending on market size, length of characteristic space .. 118
Fig. 25: number of firms for different policy settings ...................................... 120
Fig. 26: The nanotechnology value chain .................................................. 131
Fig. 27: absolute and relative appearance of capabilities .................................. 133
Fig. 28: absolute appearance of capabilities ............................................... 134
Fig. 29: Technological coherence of capabilities in IHs .................................. 135
Fig. 30: The capability network scheme .................................................... 137
Fig. 31: Example network of capabilities – high modularity ............................ 137
Fig. 32: Example network of capabilities – low modularity ............................. 138
List of Tables

Table 1: Descriptive statistics Irish patents .................................................................75
Table 2: Descriptive network statistics ........................................................................76
Table 3: Systems of innovation approaches ..................................................................84
Table 4: Parameters and initial values of the first experiment ........................................113
Table 5: standard scenario parameter settings ..............................................................132
Table 6: modularity of capability networks ..................................................................138
Abstract

Nanotechnology is expected to have major economic impact over the next decades. Due to its importance, nanotechnology has drawn the attention of policy makers. The huge impact mainly relies on its properties as a general purpose technology (GPT). GPTs can be combined with other technologies, thereby bringing about new innovations and thus feedback effects. If nanotechnology in particular and GPTs in general are of such great importance, effective and efficient policy designs aiming at the fostering of nanotechnology research, development (R&D) and innovation are of vital importance. To design these policies, it is important to understand how GPTs are affecting different technological areas. An empirical study of the knowledge structure of Ireland using social network analysis shows how nanotechnology is connected to the overall knowledge available. We find that nanotechnology is still a rather weakly connected multidisciplinary field however, showing signs of increasingly connecting technology areas in which it is applied.

Policy does, however, not exclusively focus on innovations and growth. A recent example is the normative concept of responsible research and innovation, aiming at designing policies, which solve a broader range of societal problems. It is demonstrated that the framework developed can also be used to design research and innovation policies not purely aimed at economic problems. In policy implications it is outlined that due to the great impacts of a GPT on innovation and thus on the economy, normative questions gain even more significance.

If policy aims at fostering research and innovation (R&I), it needs to consider the complex nature of R&I, the collaborations in which R&I happens and the relations within such an innovation system. To design efficient policies, these policies can be evaluated before they are introduced by applying computer simulations. With agent-based modelling (ABM) a methodology is available for developing such simulations. At the same time, these computer simulations must can reproduce complex behaviour. An ABM is developed and it is shown that policy questions, here about the importance of heterogeneity can be tackled applying agent-based simulation.

With the SKIN (Simulation Knowledge Dynamics in Innovation Networks) a promising tool for R&I policy modelling is identified. Applying a set of indicators, it is shown that the SKIN model in its current form does not capture the emergence and diffusion of GPTs. Subsequently, pathways for adaptations of the model are developed.

The work concludes by outlining policy implications and the applicability of the Systems of Innovation approach in connection to the concept of GPTs.
Statement of Original Authorship

I hereby certify that the submitted work is my own work, was completed while registered as a candidate for the degree stated on the Title Page, and I have not obtained a degree elsewhere on the basis of the research presented in this submitted work.

Dublin April 2017  
Benjamin Schrempf
Collaborations

Collaboration in science and research has become standard in most, if not all disciplines. This also applies to this thesis: the published work was completed in collaboration with various peers:

Authors:
- Benjamin Schrempf: concept, research design and questions, data generation and analysis, writing;
- Evgenia Dolgova (Leeds University, United Kingdom): comments, research design and writing

Publication 2: Responsible, Inclusive Innovation and the Nano-divide. Published 2016 in: Nanoethics (10) 177-188.
Authors:
- Doris Schroeder (UCLAN, Preston, UK): concept, research design, conclusions and writing;
- Sally Dalton-Brown (University of Melbourne, Australia): research design, writing;
- Benjamin Schrempf (EA European Academy of Technology and Innovation Assessment, Germany): section on Systems of Innovation, conclusions
- David Kaplan (University of Cape Town, South Africa): concept, research design, and writing.

Authors:
- Matthias Müller (University of Hohenheim, Germany): programming, research question, data analysis and interpretation, writing;
- Benjamin Schrempf: concept, research design, data interpretation, writing;
- Andreas Pyka (University of Hohenheim, Germany): comments and advice.

Authors:
- Benjamin Schrempf: research design and question, programming, data analysis and interpretation, writing.
- Petra Ahrweiler (University College Dublin and EA European Academy of Technology and Innovation Assessment): comments and advice.
1 Introduction

1.1 Research Problem and Relevance

‘Nanotechnology is an enabling technology that can act as an anchor for Ireland’s improved international competitiveness and will have a deep and lasting impact on current Irish businesses, as well as current and potential FDI in areas such as medical devices and electronics.’ (Forfás 2010, p. 6).

Nanotechnology is said to be one of the major forces shaping economic development over the next decades. Due to its importance, nanotechnology has drawn the attention of policy makers in many countries. Even more so in countries which have made research and innovation policy one of their main remedies for economic, and increasingly also for other societal problems.

The huge impact nanotechnology is expected to have mainly relies on its properties as a general purpose technology (GPT). GPTs possess a number of properties making them ‘engines of ‘growth’ (Bresnahan and Trajtenberg 1995). These ‘special’ technologies are widely applicable and also used in many other technology sectors. In the sectors, in which they are applied (application sectors, AS) they spur innovations and trigger the development of complementary innovations. By applying the GPT, its knowledge base is improved even further, making it even more attractive to apply in additional sectors. This ‘dual inducement’ (Teichert 2012) makes GPTs a very promising field for research and development. But also policy makers find them an attractive target for research and innovation policies since advances in a GPT possibly feed into many other sectors. Examples are numerous: taking nanotechnology as a GPT, its most prominent applications are microprocessors, for which the processing of silicon on a nanometre scale was enabled by the development of the electron microscope and its combination with knowledge and products from the electronics sector. It need not to be described how the invention of the microprocessor has influenced the world economy since its invention in the 1960s. Innovations that were only possible due to the microprocessor and can be seen as complementary to it range from the personal computer, including even the development of software, to smartphones and autonomous driving. More recent and lesser known examples are the development of living sensors by combining a living cell with a microprocessor. Here, the technology areas combined are microelectronics and biotechnology.

This in turn are already good examples of the various effects a GPT has. A major example can be identified in the microprocessor. Its development was enabled by the advances made in nanotechnology. Subsequently, the microprocessor itself could be combined with a living by again applying knowledge in nanotechnology. Hence,
nanotechnology helped to spur further innovations in microelectronics and biotechnology – two of the many application sectors of nanotechnology. It is this broad applicability in many sectors and the spurring of innovations in application sectors, amongst other properties such as the scope for further improvement and the development of complementaries, which makes GPTs such as nanotechnology a promising target for policy intervention.¹

With this dissertation I aim at laying the foundations for a computational social sciences approach to policy modelling focussing on GPTs. For this purpose, the following steps are necessary:

1. The need for developing policy measures aimed at GPTs needs to established.
2. The framework on which the policy modelling approach is based needs to be identified as suitable for the purpose of modelling different policy goals.
3. It needs to be shown that also the methodology applied suits its purpose for representing knowledge, simulating and assessing policy questions.
4. An existing simulation platform is to be identified and investigated whether GPTs can already be modelled without adaptations.

1. The necessity for developing policy measures aimed at GPTs needs to be established: If nanotechnology in particular and GPTs in general are of such great importance, effective and efficient policy designs aiming at the fostering of nanotechnology research, development (R&D) and innovation are of great importance. In order to design these policies, it is important to understand
   - How is GPT/nanotechnology affecting different technological areas?

   With an empirical study this question is tackled by analysing the knowledge structure of Ireland and investigates how nanotechnology is connected to the overall knowledge available.

2. The framework on which the policy modelling approach is based needs to be identified as suitable for the purpose of modelling different policy goals.

   In many cases, R&I policy purely aims at fostering economic growth via innovation activities. In the last years, new policy goals focussing not exclusively on innovations and growth are discussed and introduced.² Most recent example is the normative concept³

¹ Please see later chapters for a more detailed definition of GPTs and its theoretical foundations.
³ Please see Chapter 2.2 for a more detailed discussion of the term.
of responsible research and innovation, aiming at designing policies, which solve a broader range of societal problems. The next question therefore is

- Can a Systems of Innovations framework, which understands innovation as an evolutionary process taking place in a complex social system also be used to design research and innovation policies not purely aimed at economic problems?

3. *It needs to be shown that also the methodology applied suits its purpose for representing knowledge, simulating and assessing policy questions.*

Modern technologies are already very complex and no single individual is able to do meaningful research and innovation in any field on its own. This is even more so for GPTs, which mostly are applied to another, distant technology. If policy aims at fostering R&I in any technology, it need to take into account the complex nature of R&I, the collaborations in which it happens and the relations within such an Innovation System. In order to design efficient policies, one way to evaluate and align these policy measures before they are introduced is by applying computer simulations. With agent-based modelling, a methodology is available for developing such simulations. At the same time, these computer simulations must be capable of reproducing complex behaviour. Furthermore, for eventually being able to capture the singularities of GPT knowledge, a representation of knowledge must be at the core of the simulation. The next question therefore is:

- How can knowledge be represented in an ABM in order to develop and evaluate policy questions?

Methods established in innovation systems research, such as social network analysis and agent-based modelling, may thus be applied for assessing the introduction of policy measures based on normative concepts.

4. *An existing simulation platform is identified and investigated whether GPTs can already be modelled without adaptations.*

Finally, with the SKIN (Simulation Knowledge Dynamics in Innovation Networks) a promising tool for R&I policy modelling is identified. Should this tool already be capable of reproducing the main traits of GPTs, it would be the simulation platform of choice. The last question therefore is:

- *Can GPTs already be identified in the SKIN model, and if so, how?*

The last chapter therefore is the foundation for further research in the direction of policy modelling for GPTs: An attempt is made to find a way to model the dissemination of a GPT within the reduced SKIN model. This is to pave the way for further research into how GPTs can be made an emergent phenomenon in the SKIN, for which some model
adaptations are outlined. This model would then provide a sound basis for policy modelling in order to tackle the questions asked in Chapter 5.2.

1.2 Structure of Dissertation

In order to tackle the research questions outlined, the steps as described in the following were taken for this dissertation. The main part of the work consists of six parts. Fig. 1 illustrates how the overall work is structured and how the individual parts are linked to one another. Chapter 1 of this work states the relevance of the research problem and the overall research questions. Subsequently Chapter 2 introduces the overall theoretical framework, which is set by the non-linear, neo-Schumpeterian approach to innovation, the theory of systems of innovation and complex systems. Finally, an overview of the state of the art of scientific literature on general purpose technologies is given.

In Chapter 3, the research methodology is laid out. This comprises the research design, the conceptual framework with detailed research questions and the main methods used: social network analysis (SNA) and agent-based modelling (ABM), and specifically the SKIN model are introduced.

The data used for the empirical study and model validation is introduced in Chapter 4. Chapter 5 mainly contains work already published. First, an empirical study based on the Irish nanotechnology sector shows how social network analysis can be used in order to reveal the structures of networks, in this case the Irish co-classification patent network. It reveals how nanotechnology related patents are intertwined with other technologies present in the Irish patent network. Some of the main findings are used in chapter 5.4.

Publication two develops a nanotechnology-related policy question which could be addressed using the tools of the systems of innovation approach. Normative concepts, such as inclusive innovation and responsible research and innovation can be linked to the descriptive systems of innovation approach.

In the third publication in 5.3 an agent-based simulation model of knowledge representation is developed and applied to the question of influences of demand on innovation. The aim of the paper is a methodological one, which is to show how knowledge may be represented as bit strings. It concludes with the development of policy questions, hence showing that already a rather simplistic representation of knowledge and the simulation of different scenarios may be used for policy modelling.

Publication number four refers to the SKIN model introduced in section 3.5 as an accepted simulation platform for policy modelling. Using a set of theory-based indicators for general purpose technologies, the SKIN model is analysed. It becomes evident that an emergence of general purpose technologies cannot yet be modelled with the standard SKIN model.
With the last section in Chapter 5 – which is unpublished work – it is outlined how GPTs may be introduced in the SKIN model. Based on some simulation results it can be shown how these technologies may diffuse along value chains emerging in the SKIN model dependent on effects GPT knowledge exerts on products.

In Chapter 6 the results are summarised and an overall conclusion is given. Furthermore, limitations of the research conducted as well as limitations are outlined. The last section concludes with proposed paths for further research.

Fig. 1: Structure of work
2 Theoretical Framework

Nanotechnology is a typical example of a knowledge intensive technology. Additionally, it has a wide range of applications, making it a general purpose technology (Youtie et al. 2007). In some areas, nanotechnology products are already being commercialized on the market, in other fields, research is still in early stages. This research in nanotechnology is conducted by many different actors, like universities, public research laboratories or R&D departments of companies. At the same time, governments are investing large sums to promote research, development and innovation in nanotechnology, e.g. by trying to foster the creation of research networks (Rossi 2005). In this chapter, an outline of the theoretical foundations of innovation theory as it developed to the current stage and its connections to approaches on complex social systems is outlined. Subsequently the networks perspective on innovation is elaborated, underlining the importance of collaboration for generating new knowledge. This section is followed by an outline of the SI approach as the analytical framework for policy modelling. The chapter concludes with an overview of the theory of GPTs.

2.1 From Neo-classical approaches to the chain-linked model of innovation

Within the evolution of models of innovation, the importance of knowledge for the innovation process varies greatly, so does the degree of complexity associated with the innovation process itself. In literature, mainly five or six generations of innovation models can be identified (Rothwell 1994, Marinova and Philimore 2003) – however, there is no consensus on how the exact number of innovation model generations there are, nor how these generations should be named (Barbieri and Álvares 2016). In the following, an introduction into the main models of innovation is given and their shortcomings, especially regarding their conceptualisation of knowledge are discussed.

According to Marinova and Phillimore (2003), the black-box model of innovation, drawing from the tradition of neo-classical economics can be regarded as the first generation of innovation models. In this model generation, the first attempts were made to internalize technological progress into the production function and thus explaining one major driver of economic growth. Hence, in neo-classical theory growth theory (Solow 1956) production and thus growth is dependent on a limited number of factors, such as work, capital and technology.

Even though technological progress has been endogenized in new growth theory (see below), technology and thus its underlying knowledge is mostly modelled in a very simplistic way. Also, the changes technology is experiencing is either modelled as an external variable or simply dependent on factors such as resource allocation. The theory
pretends that firms also have enough knowledge about current and future prices of input factors as well as products, and thus can choose their technology to maximize profits. Technology in this sense is, as knowledge, easily, rapidly and cheaply accessible. Hence, the technology dimension is regarded as being unproblematic, a simple input factor. This rests on several strong assumptions about knowledge in neo-classical economics: a) knowledge is generic, which means it can be easily applied to very different sectors, b) it is codified and thus can be transmitted easily, c) knowledge is also available without significant costs, which means no costs for transmission or bringing the knowledge into production occur and d) it is context independent, enabling all firms to bring it into production. These assumptions present knowledge as unproblematic to acquire and to operationalise. However, they in turn make it problematic to model the development of technology and new technological principles (cf. Smith, 2000).

In contrast to the neo-classical approach the role of knowledge is at the centre of analysis in the New Growth Theory. Here, Arrow (1962) and Romer (1990) argue, that knowledge is flowing between the actors involuntarily, creating so called knowledge spillovers. The knowledge can thus be used by many actors, leading to increasing returns of scale. With this attempt, new growth theory tried to integrate knowledge in the neo-classical production function, which was necessary to explain persistent economic growth despite decreasing returns from the production factors of labour and capital. However, this notion of knowledge also leads to low incentives for firms to invest in research, as they cannot fully internalize the profits from the results generated. Thus, Nelson (Nelson 1959) and Arrow (1962) (‘Nelson-Arrow-Paradigm’) outline two main arguments for public market intervention: first, the inherent uncertainty of knowledge creation means that the output of this process is not predictable based on the inputs to the process. Second, due to incomplete appropriability, which means that if producers cannot appropriate the benefits from the knowledge they produced, firms have a socially sub-optimal incentive to invest in knowledge creation. Knowledge in the view of Arrow and Nelson is also indivisible, which means knowledge and hence the goods produced with it must exist on a minimum scale.

In this generation of innovation models, the innovation process itself largely remained unexplained and what was considered important was the input factors and the results that were generated based on these inputs and the appropriate and timely management of these resources (Rosenberg 1982). In this sense R&D the importance of R&D was acknowledged, but how the innovation process exactly worked remained a black box. With the ‘linear models of innovation’ a very simple and clear relationship between basic research, leading to applied research and finally to the development and diffusion of new products was promoted in literature over a long period of time. These model were not
‘spontaneous invention arising from the mind of one individual’ (Godin 2006, p. 33) - in this case Vannevar Bush (1945) - but were developed over three time steps which correspond to the policy implications connected to them: first, the importance of governmental support to basic research, second, the importance of technology for the development of new products in industry and third the effects of basic and applied research on the economy by the diffusion of new products and innovations.

Beginning with the technology push-model, which is often regarded as the first generation of innovation models (Rothwell 1994) or the first linear innovation model (Tidd 2006), innovations emerge stimulated by the results of the R&D process on which a discovery is made. This process mostly takes place in private public research entities, producing a constant stream of novelties flowing from basic research to the market (Barbieri and Álvares 2016). Based on a discovery made within an R&D entity, e.g. a prototype is developed and brought to a marketable level. It is then manufactured and marketed. The linear process ends by selling the innovation on the market and in this sense, the innovation (which is mostly based on technology in this model) is pushed to the market (Rothwell 1994).

The second generation of linear models of innovation, or market/need pull model (Fig. 3) (Rothwell 1994), represents an early but still very commonly employed model of the creation of new knowledge and the introduction of innovations into markets. In this model, ideas stemming from the market, which are in turn based on demands (Rothwell and Zegveld 1985) are triggering the innovation process.

Central characteristics of both linear approaches are: i) the technological frontiers of an economy are defined by the available knowledge. By conducting research, these frontiers can be expanded, ii) the knowledge relevant for production is transferred
scientific knowledge and defined by this scientific knowledge, iii) this transfer process is sequential, iv) the linear model is a technocratic approach in which technological change can be implemented in an engineered way (Godin 2006).

Both linear models, the technology push as well as the market pull approach only provided an over simplification of the connections and interdependencies between science, R&D, the technology and the marketplace (Rothwell 1992). Also, considering questions of how the diffusion of knowledge works, how knowledge is actually generated and how actors may proceed from the creation of new knowledge and the recombination of existing knowledge to innovation is missing in the linear model (Estók 2001, Ahrweiler 2010).

Furthermore, the linear model not only makes inappropriate assumptions about knowledge, which it inherits from neo-classical economics, but also insufficiently models the process how innovation is generated and diffused:

1. No feedback loops are considered, neither from the development to science process nor from sale to development or design. But these feedback loops are important for e.g. knowing in which direction the next step in development should go. Feedback is also essential for learning (learning by feedback). Development is a mere evolutionary process, which is done best with many divergent sources of information to cope with the uncertainty connected to development.

2. Design and thus the creation of an innovation, follows in a linear way from research. Often, however, the design of a product demands for new science to be conducted, e.g. if a product is in need of a new material. In reality there is no linear relationship but basic research, applied research and product development are influencing each other in various ways.

3. Innovations are also possible without having a full scientific understanding about the processes the innovation they are based on. This is connected to a learning-by-doing process in which incremental changes can lead to new innovations, without having fully understood the basic science behind it (Kline and Rosenberg 1986).

It is also argued that both factors, technology and market may play an important role in the innovation process at the same time with their relative importance depending for instance on the phase of respective industries’ cycle (Rothwell 1992). Furthermore, the linear models of innovation both assume that “the cost of scientific inquiry raises faster than the returns from it” (Rescher 1978, p. 2). This would mean however, that there is an intrinsic limit to scientific research and that at some point, more research would not create further innovation: the innovation system would stall (Godin 2005).
In both, the first generation (in the neo-classical theory of knowledge or black-box model) and the second generation (linear models) of innovation models, there are several assumptions, which are not reflected empirically. Compared to neo-classical assumptions on knowledge stated above, first, it turns out that knowledge in knowledge intensive industries is highly complex and very firm and product specific, making it very difficult to transfer it to other areas. Second, the most relevant knowledge is rarely codified but seems to be in the skills of the individuals, thus this knowledge is tacit and cannot be transmitted easily. Third, the tacitness and specificity of knowledge make it expensive to access by other actors. And finally, the knowledge is bounded, i.e. each firm has a more or less clear area of competence and not all firms have the same competence in bringing knowledge into production (Godin 2006). Also, the model makes strong assumptions e.g. on representative agents or pure market coordination of resource allocation (Estók 2001) and also justifies public intervention in the innovation process (Godin 2006b) e.g. via innovation policies on the same grounds as neo-classical theory.

With the chain-linked model (Fig. 4) a more sophisticated model can be found in literature. This model takes into account some of the shortcomings of the linear model (Kline and Rosenberg 1986) such as the over-simplification of the complex processes and interactions between the building blocks of the system such as science R&D, the market but also knowledge and technology.

![Chain-linked model](image.png)

Fig. 4: Chain-linked model according to Kline and Rosenberg (1986)
The chain linked model by Kline (1985) and Kline and Rosenberg (1986) is a later stage model of the third generation of innovation models, also described as combined, coupled or interactive models. At its core, the main building blocks of the linear models can be found. Furthermore, the model underlines the complexity of the innovation process and the relationships between the different stages and elements. (Kline and Rosenberg 1986). Socio-technological aspects of industry and technology are emphasized. In the model, there is no clear ‘starting point’ of the innovation process, which can be linear but also iterative, including feedback loops between all building blocks and stages of the process. In this sense, the chain linked model combines aspects of technology push and market pull models, as well as top-down and bottom up-processes. This greatly underlines the importance of interactions between the various components of the innovation system (Micaelli et al. 2014) and aspects of networks between actors (Rothwell 1994).

Even though the chain linked model can be regarded as a more comprehensive model if innovation, integrating both, the push and the pull model of innovation and combining them with interactive and networking aspects (Meissner and Kotsemir 2016), as well as with giving knowledge a greater emphasis, there are still various shortcomings in the chain linked model (Micaelli et al. 2014):

- There is no consideration of interactions with the environment, only within the various building blocks of the innovation process.
- Furthermore, interactions are not considered between different innovation systems (e.g. in other places) and there is no description of the actors in the system (e.g. who is performing the innovation),
- The chain link model only considers the dynamics of an innovation process itself, which is however insufficient for describing an entire innovation system.
- It lacks a detailed representation of the output generated in the innovation process.
- In the model, knowledge is given a greater emphasis and is considered an integrative element (Bonjour and Micaelli 2010) which is connected directly to all other elements. However, it is still represented in a very simplified way, simply as a box called “knowledge” (Micaelli et al. 2014). The model does not explain for example how knowledge is generated, shared and learnt (Meissner and Kotsemir 2016).
- There is a lack of explanatory power in the model concerning the drivers of the innovation process, the reasons why some companies and innovations are more successful than others (Meissner and Kotsemir 2016).
Based on these shortcomings, in the early 1990s, with the system of innovation and later with evolutionary and complexity modelling approaches, attempts were made to overcome these issues.

2.2 The Neo-Schumpeterian framework

By taking the interaction between actors and e.g. recursions into account, the basic linear model could be extended. However, this still does not capture important aspects of innovation, such as network effects or different characteristics of knowledge and its creation. The chain-linked model of innovation already mentions the importance of collaboration, but how these collaborations are established, what their consequences and what the limitations on collaborations are remains unclear. Furthermore, knowledge representation remains underdeveloped. Also, the innovation process itself cannot be explained accordingly with the approaches to innovation mentioned above. Questions of how innovations actually emerge, of how they disseminate, of what the activities are taking place in the economy in order to generate innovation, of how the innovation system as whole is interconnected, and of how policy can influence the innovation system for reaching certain goals remain insufficiently answered. As stated above, the neo-classical school of thought was not only unable to adequately describe the innovation process in a firm, it also failed to adequately incorporate true uncertainty within the innovation process, the interaction of heterogeneous actors (such as small and large firms, firms in different sectors, research institutes) with different capabilities, skill sets, or capacities to learn and apply new knowledge. The importance of these aspects will be elaborated in more detail in the following two chapters.

In neo-classical economics, optimization e.g. in terms of resource allocation plays an important role and is prerequisite for rational decision making by the *homo-oeconomicus*. This representative agent makes decisions in order to maximize his utility function based on perfect information and foresight. Representative decisions made at the micro-level are then aggregated and analysed at a macro-level. However, long-term dynamics of the economy can hardly be analysed or even predicted with this approach since they very often rely on unforeseeable technological developments. It is inherently impossible to predict the results of an R&D process, even more so its effects on certain sectors or the entire economy. Decision-making based on foresight and rational expectations is thus rendered impossible (Verspagen 2002).

The acknowledgement that these over-simplified assumptions of neo-classical economics have to be neglected for better understanding long-term evolutionary developments in the economy – which bases mainly technological innovations – gave rise to the ideas of bounded rationality and a non-representative agent acting under true
uncertainty and economy in which the equilibrium state is rather the exception than the rule (Verspagen 2002).

Evolutionary economics has path dependencies and feedback-effects at its core and is said to be considering mainly evolutionary development in the long run. Thus, with an increase of the time span under consideration, uncertainty increases. Also there is a high number of random factors, and, similarly to biological evolution, contingencies in the economic process may bring about change and thus evolutionary paths which have been unforeseeable. Evolutionary economics draws on another idea from biology: A population of heterogeneous actors interacts, reacts to developments within the systems, and is selected e.g. for survival by a selection mechanism, leading to dynamics within the population. In evolutionary economics, each actor has its own competitiveness function based on which actors make their decisions, and thus the competitiveness function determines their behaviour (Verspagen 2002).

Nelson and Winter (1982), who coined the term evolutionary economics, also state that their approach could be labelled as neo-Schumpeterian, in the sense that their evolutionary approach can help to formalize the Schumpeterian view on economics (Nelson and Winter 1982). Hanusch and Pyka consider the works of Schumpeter as one of the intellectual roots of evolutionary economics. An important aspect of evolutionary economics which feeds into the neo-Schumpeterian view is the consideration of historic time. Thus path dependencies, feedback-effects, the emergence and diffusion of knowledge and innovations, openness to future developments, learning and cognition of bounded rational actors, heterogeneity as well as uncertainty are all taken into consideration (Hanusch and Pyka 2007) and will be developed further in the following chapters.

The main aspect of this approach traces back to the works by Joseph Schumpeter (1912, 1942), who puts novelties and thus innovation at the centre of his analysis. It is novelties which bring about economic development by the process of ‘creative destruction’. The novelty is brought into the economy by the entrepreneur, who takes the risk of failure in turn for the chance of profiting from a temporary monopoly (Schumpeter 1912). In his second main work, Schumpeter shifted his focus from the entrepreneur to R&D departments of large enterprises (Schumpeter 1942). Growth in this sense is driven by innovation, accompanied by structural change, which is caused endogenously by actions and interactions of agents, such as knowledge generation and diffusion (Hanusch and Pyka 2010).

Innovation is at the core of NSE since it is regarded as the driving force behind economic dynamics even replacing the finite competition based on price with a limitation-overcoming competition based on innovation (Hanusch and Pyka 2006). Thus, if
innovation is the basis for competition, true uncertainty becomes a central factor of the economy. Risk, which can be calculated based on assumptions concerning e.g. price distributions and customer preferences – which are a finite set of possibilities – cannot be calculated any longer since innovation delimit the set of possible options, thus introducing real uncertainty in a Knightian sense (Knight 1921). By placing innovation and with it uncertainty at its core, the neo-Schumpeterian approach can be regarded as future-oriented (Hanusch and Pyka 2006).

Innovation is at the core of the NSE approach. Hanusch and Pyka (2006) even go as far as claiming that innovation (technological, organisational, social, and institutional innovation) in neo-Schumpeterian economics is the normative principle. They contrast NSE to neo-classical economics, in which optimal allocation and efficiency within the given constraints is at the core of the framework. In NSE the removal of these constraints by ways of innovation, thereby enabling economic development, is the main goal, and in this sense innovation can be seen as the normative principle (Hanusch and Pyka 2007a).

Given this normative role of innovation, Hanusch and Pyka (2007a) state a consensus over three elements of neo-Schumpeterian economics exists among scholars:

1. Constraints have to be lifted for innovation to happen at all three levels of the economy: micro, meso and macro. At all of these levels, qualitative changes happen triggered by innovation.

2. These qualitative changes do not occur in a continuous manner but in phases of relative stability and phases of radical change (Hanusch and Pyka 2007a) which is often associated with the emergence of GPTs (see subsequent chapters).

3. Patterns form at the meso and at the macro level due to non-linearities and positive feedback effects (spontaneous structuring) based on qualitative changes (Hanusch and Pyka 2007a) (see next Chapter for a detailed description of these processes).

According to Dopfer (2005), the three levels of analysis – micro (e.g. firms and entrepreneurs), meso (e.g. networks) and macro (the system level) – can be considered as the three pillars of NSE. Agents and their behaviour at the micro-level constitute a unit at the meso-level. These units in turn are the building blocks for constructing the macro-level (Dopfer 2005). With regard to the importance of innovation and knowledge in NSE, capturing dynamics which can empirically be seen at the macro-level - for

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4 We define a normative concept as a concept which would encompass a desired state or outcome (e.g. justice) and may implicitly or explicitly have prescriptive force. As such, it differentiates itself from purely descriptive concepts.
example emergent processes such as catching-up processes or forging ahead — or at the meso-level — industry sectors in different stages of maturity — can be explained by considering knowledge generation and diffusion processes at the micro-level. Thus, what can be described at the meso-level can be explained at the micro-level, which otherwise (i.e. within the neo-classical approach) would not be possible (Dopfer 2001, Carlsson and Stankiewicz 1991).

NSE emphasizes that quantitative as well as qualitative growth is mainly driven by innovations. Therefore, the framework is suitable for the analysis of learning and entrepreneurial activity at the micro-level. Industry dynamics and the emergence of networks at the meso-level, which are caused by micro-level action, manifest themselves e.g. in technological life cycles as well as in growth at the macro-level (Saviotti and Pyka 2004). All these phenomena are either closely connected to or determined by innovation (Hanusch and Pyka 2006, 2010). With innovation at its core, in NSE / the evolutionary approach the following main areas of interest are studied and may be considered as the defining concepts of the approach (according to Hanusch and Pyka (2007a):

- Entrepreneurs, Firms and Networks: The entrepreneur is regarded as the vehicle which brings innovation into the economy and therefore plays a central role in the NSE approach. The importance of the entrepreneur triggered numerous studies in management science where e.g. different forms of management are assessed for supporting entrepreneurial activities in firms. The importance of networks is stressed in evolutionary economics as should become sufficiently clear in course of this work. Furthermore, firms are considered as the “carriers of production techniques and productive knowledge” (Rahmeyer 2007, p. 167) and, due to true uncertainty concerning their environment, act based on bounded rationality (Rahmeyer 2007). Therefore, firms are analysed from different perspectives: i) behavioural perspective, analysing e.g. their strategic decisions in making processes, ii) resource-based perspective asking for their resource allocation under uncertainty, iii) knowledge perspective asking how firms may learn and turn new knowledge into innovations. (Rahmeyer 2007). With the neo-Schumpeterian / evolutionary approach, the main object of analysis changes from markets and production factors to firms, entrepreneurs, and networks (Etzkowitz and Leydesdorff 2000).

- Knowledge and Competencies: Innovations are only possible based on the recombination of existing and the acquisition of new knowledge. Tacit and codified knowledge and their consequences for knowledge generation and diffusion, global technological progress vs. the localized technological progress, and the consequences for the spillover of knowledge within localized networks
and their effect on investments in R&D, which will be sub-optimal, the role of specialisation for increased heterogeneity, which in turn is a source of new knowledge (Metcalfe 2002), and the interaction-coordinating role of institutions for the knowledge sharing process (Nelson & Winter 1982) and the notion of knowledge as an asset of firms and which can be shared e.g. by collaboration with networks or clusters (Helmstädter 2007).

- **Innovation Process and Patterns:** Despite innovation being unforeseeable and based on a trial and error process, technological trajectories and patterns of technological evolution emerge e.g. cumulative learning processes, or the symbiosis between technological progress and the R&D strategies of firms (Malerba 2007). Innovation networks based on the collaboration strategies of firms are also considered an emerging pattern (at the meso-level). Furthermore, the patterns of innovation diffusion are also of great interest in evolutionary economics (Stoneman 2007). A more detailed discussion of the networks aspect of innovation is will be provided in Chapter 2.4.

The neo-Schumpeterian approach also has implications for R&D policy making: First, if one refrains from neo-classical economics, simple market failure can no longer be used to justify market intervention by the state (Cantner and Hanusch 1997). It will rather be the innovation process itself and its processes of search and trial and error which should be the object of public policy intervention (Cantner and Pyka 2001). In the neo-Schumpeterian / evolutionary view, markets are the selection mechanism (just as e.g. in biological evolution, food supply is for the selection of the fittest) for innovations. From this it does not follow that policy may neglect to ensure the existence of functioning markets, e.g. by tackling the emergence of monopolies. However, the reasoning behind policy intervention is not optimal resource allocation as in neo-classical economic thinking, but ensuring that sufficient heterogeneity is kept in place maintaining the innovation process vivid (Metcalfe 1995). This opens up another trade-off for policy makers: On the one hand, heterogeneity is the main source for innovation (Hanusch and Pyka 2006). On the other hand, too much heterogeneity among actors may prove an obstacle for a quick and efficient diffusion of innovations within the system (Cowan and Foray 1997) – a problem which will be discussed in more detail in Chapter 5.2.

Second, the importance of true uncertainty inherent to the innovation process may serve as another argument for policy intervention. Here, questions about appropriate structures for supporting the innovative process arise, e.g. by the provision of venture capital (Cantner and Pyka 2001). Of course, true uncertainty may not be tackled by public intervention. The consequences of it may, however, be moderated by setting up and
supporting the development of structures helping to cope with the risk associated with true uncertainty.

The importance of institutions has also been stressed above and will be discussed in more detail in Chapter 2.5. Establishing reliable, efficient, and effective institutions may also be a matter of public intervention. Supportive institutions for fostering innovation may enable and support the exchange of knowledge, the establishment of collaboration networks, and they may provide an appropriate framework for ensuring investments in R&D to result in a rate of return which is supportive for further investments, without facilitating the establishment of monopolies.

With bounded rationality, heterogeneous agents and their heterogeneous knowledge, in contrast to the neo-classical homo-oeconomicus and in contrast to disequilibrium dynamics (Verspagen 2002), the neo-Schumpeterian / evolutionary approach overcomes some of the main critical issues of neo-classical economics. Innovation is based on the creation, diffusion, and recombination of this knowledge, therefore the analysis of how knowledge is structured, generated, and diffused is central to this approach. In contrast to neo-classical economics, knowledge is treated as being tacit, local, and complex. This is in contrast to neo-classical economics in which knowledge is simply a public good. Elements of complexity science may help to describe and understand these aspects of innovation, as stated in the next section.

2.3 Complexity and Innovation

Several attributes of great importance in evolutionary or neo-Schumpeterian economics can also be found in the wider framework of complexity science (Robert and Yoguel 2016), which is why evolutionary or neo-Schumpeterian economists have found great interest in using the tools already in existence in complexity science in their own field of study (Frenken 2006, Durlauf 2005).

The framework of evolutionary theory and neo-Schumpeterian economics is useful to understand how technological change influences different sectors and how dynamics at the meso- and macro level can be explained. However, there are still several aspects of innovation, which cannot be captured so far (Frenken 2006).

- While it is possible to analyse the different states of an economy and assess their structures and dynamic changes, it is not yet possible to explain how this change exactly happens.
- Knowledge has different forms, can be of different grades of complexity and can be exchanged. However, we cannot yet capture how knowledge enables the generation of new innovations or how it can be exchanged.
Also, an explanation of how new knowledge and innovations emerge and how they disseminate cannot yet be given. (Ahrweiler 2010)

One way to capture all these aspects is with the help of complexity theory: the approach helps to describe, to analyse and to understand aspects originating from natural systems such as uncertainty in the knowledge creation process, non-linearities in the growth of new innovations, path dependency in the adoption of new technologies and emergence of network structures (Frenken 2006). However, the transition from natural sciences to social sciences is possible as social systems show enough similarities to allow for the application of complexity theory (Ahrweiler 2010).

Complexity science emphasizes the interaction between agents in the process of knowledge generation and diffusion. Complex systems, in contrast to simple systems, are characterized by positive and negative feedback effects, decentralized structures for decision making, are irreducible and their behaviour is unpredictable. (Hanusch and Pyka 2007). Saviotti (2010) argues, a prediction of emergence and the changes in the structure of a social system is in principle possible with complexity science methods, but only by precisely considering the specific characteristics of the respective system.

Innovation can be regarded as a complex phenomenon in which the term ‘complexity’ can refer to the complex interaction between actors of a technological system as well as to the interaction structures within an innovation network. According to Frenken (2006) three main research lines can be identified in the literature: fitness landscape models, percolation models, and complex network models. For the purpose of this thesis, the latter, complex network models, are most important, as networks – between actors or between pieces of knowledge – can be considered one of the most important characteristics in knowledge intensive industries.

Networks can be described as a non-trivial graph with nodes and edges, where nodes are elements and edges represent interactions or relations. Agents in these networks interact in complex ways, and can follow a strategy thereby leading to innovation. The performance of such networks is influenced by the structure of the relationship of the agents. Similar to neo-Schumpeterian economics, in complex systems approaches many assumptions of common economics are given up, such as homogeneity of actors or pure market interaction (cf. Frenken 2006). The degree of complexity can be changed by just altering one parameter, which makes it possible to generate solutions (e.g. by simulation) which cannot be obtained analytically.

In this sense, methods from complexity science are also applicable to complex social systems. By taking into account phenomena like uncertainty, feedback loops and strategic behaviour, complexity science approaches can help to explain how systems change, it can also help to explain how new components and interactions along with any
change in existing ones can lead to the emergence of novelties. Complexity science can thus help to understand how knowledge is generated and diffused, for example within a complex network.

As Andriani (2011) argues, knowledge in addition to capital or labour can be regarded as an important factor for production, additionally it also is the central factor for innovation. Unlike other factors, knowledge shows positive feedback and network effects, is prone to non-linearities and thus leads to discontinuous change. Innovations based on this knowledge are also characterised by nonlinearities, path-dependencies, emergence and self-organisation. With concepts from complexity science, it is possible not only to describe these properties but also to understand them and, by the use of methods of complexity science, also to model innovation processes. According to Andriani (2011) concepts similar to those of complexity science were already introduced to innovation theories by Schumpeter (1939). These concepts include chaos in the process of innovation, extreme events and bottom-up processes, which are in turn at the core of Schumpeter’s ideas on entrepreneurship.

Furthermore, Andriani (2011) classifies the literature on complexity and innovation into two major groups. Rejecting the linear idea of innovation (c.f. Godin 2006) as it is incorporated in neo-classical economics, the first group focuses on the emergence of innovation, underlining the importance of evolutionary properties, path-dependency and self-organisation. The focus of this literature mainly is on the modelling of discontinuities, which are often triggered by radical innovation. From radically new innovations, new dominant designs (Abernathy and Utterback 1978) and technological trajectories (Dosi 1982) can emerge, giving rise to the notion of an evolutionary development of the economy (Nelson and Winter 1982).

The second strand of literature has a focus on networks, either emphasizing the role of collaborations and knowledge diffusion on innovation (Powell et al. 2005), or investigating the connection between network topology and diffusion (Cowan 2004). Networks in both streams can have various actors, ranging from organisational entities such as companies or universities (Gay and Dousset 2005), to citations in patents (Jaffe et al., 1993) and patent co-classifications (Dolfsma and Leydesdorff 2011). Innovation networks consisting of heterogeneous actors became a persistent phenomenon in the economy and have become a major object of research. With standard economic theory being hardly able to explain their emergence and persistence (Pyka 2002a), alternative approaches to innovation have gained more interest.

As stated above, also methods of complexity science prove to be helpful, especially in analysing and simulating such networks. Adriani (2011) identifies various contributions of complexity science to the analysis of networks, by i) explaining the non-randomness
of network structures (scale-freeness and small worlds (Watts and Strogatz 1998), ii)
connecting networks structures to innovation processes and iii) linking the self-
organisation of networks structures with their flexibility and diversity.

A further connection between the complex systems approach and innovation studies lies
in power-law distributions. In complex systems, such as complex networks (Barabási et
al. 2008) this type of distribution very often emerges as a regularity from the interaction
of the elements at the micro level. The same distributions can be found empirically in
innovation systems, e.g. in the distribution of degrees, i.e the links per node in innovation
networks (Pyka and Scharnhorst 2009). Furthermore, power-laws describe best the
distribution of the impact on the economy of: Only a very small number of innovations
show greater effects while the large majority of innovations develop a minor overall
economic impact. Innovations with large impact often need to be combined with other,
compatible innovations and can thus be considered as GPTs. As stated in Chapter 2,
such rare innovations then often affect unrelated markets by new applications. This may
lead to a swarm-like emergence of new companies and markets, resulting in a new layer
of complexity and interdependence (Andriani 2011). This again underlines the approach
to treat the analysis of GPT innovation different from other technologies.

In the following, some of the most important characteristics (emergence, path-
dependence, interdependence and heterogeneity) are described and examples are
given to underline the connection between complexity theory and technological
innovation within networks.

- Emergence

“Emergent properties are properties of a system that apply at a specific level of
aggregation of a system” (Antonelli 2009 p. 635). Axtell (2007) regards emergence as a
main mechanism in a complex system, which is important in different systems, ranging
from physics to biology and social systems. Within structures consisting of many
heterogeneous agents, new properties arise at a higher level (e.g. the meso-level) by
the interaction of these agents, while these properties are non-existent on the lower level
of the agents. Long-lasting multi-agent structures are the prerequisite for the emergence
of such higher-level properties over a longer time (Axtell 2007). Together with self-
organisation the behaviour and interactions at the micro-level result in the spontaneous
structures and dynamics at the macro-level (Martin and Sunley 2007). Beinhocker (2006)
sees this is one of the major differences from traditional neo-economic thinking, in which
micro- and macro-economics are largely analysed separately or, as stated above, by
aggregating the micro-level to analyse macro-level patterns.
According to Kauffman (2000) emergent order and thus innovation at the meso-level cannot be explained by pure selection within the evolutionary process. It is the intentional interaction of actors – in order to learn from each other and create novelties (Gilbert et al. 2001a) – which may cause innovations or order at a higher level (such as networks) to emerge. Antonelli and Ferraris (2009) argue that the pure (inter)action of agents is not sufficient for innovations to emerge. This can only be achieved if system conditions, i.e. conditions external to the system and complementary systemic conditions, additional to individual, intentional activities are taken into account and seen as complementary. Innovation can only emerge if agents seek to profit from changing conditions in the market they target by successfully introducing an innovation. In this way, intentional activities explain the emergence of innovation endogenously as the consequence of the reaction of agents to changing system conditions (Antonelli 2009).

Besides innovation, there are numerous other emergent properties which are important within the field of innovation studies: network structures (Pyka and Saviotti 2002), industries (Hanusch and Pyka 2007b), technological trajectories and paradigms (Dosi 1982a), norms (Dosi et al. 1999), and technological regimes (Malerba and Orsenigo 1997, Malerba 2007). At the macro-level, aggregate growth rates are another example of emergent phenomena based on the interaction of industries (Metcalfe et al. 2003, Beckenbach and Briegel 2010) caused for instance by innovation.

With respect to the emergence of nanotechnology and the downstream innovations its emergence triggered, Bonifati (2010) emphasizes the link between the quantitative change in scale of potential production which can lead to qualitative changes in production, technology, and markets. The potential scale may change because of a) new technology raising the efficient scale of production, b) intentional action by entrepreneurs to create new markets, or c) expansion of markets through institutional factors (e.g. free trade). The author argues that a change in scale leads to the emergence of properties which cannot be derived from the original system. With nanotechnology being applicable in many fields, the concept of ‘more is different’ can easily be seen to apply to nanotechnology, for instance in the semiconductor industry. Nanotechnology enabled a continuous decline in microprocessor prices. The quantitative increase of the scale of potential production by applying nanotechnology in an ever-increasing number of technology sectors (increased potential markets) facilitated a qualitative change of the technology (e.g. through ever-smaller microprocessors) by investing in R&D and bringing up new innovations. In this sense, a quantitative change in scale led to the emergence of qualitatively new properties.
• Path dependence

Path-dependence is another characteristic which innovation (networks) and complex systems have in common (Foster and Metcalfe 2009). Path-dependence means that the evolution of a system is at least partially determined by past events (Niosi 2011). The development and outcome of a path-dependent system is not only determined by its initial conditions (deterministic path-dependence), but also by the events that are happening along the development path (Antonelli 2009), thus leaving room for agency and external influences. Path-dependence also can be seen in many aspects of innovation which was already underlined by Schumpeter (Dosi 1988): innovations made by a firm are determined by the firms’ production factors and by the accumulated (tacit) knowledge it has (e.g. gained by learning by doing/using). Also, the diffusion of innovation can be path-dependent, meaning that an innovation, which has already been adopted by many other firms will be adopted by others to gain from increasing returns to adoption. Further distinctions can be made between internal or individual and external path-dependence. In internal path-dependence factors internal to the organisation such as accumulated knowledge or absorptive capacity determine the path. Here, especially tacit knowledge plays a crucial role as it cannot be acquired easily and has to be built up by learning, which in turn is determined by the absorptive capacity of an organisation. For individual path-dependence local interactions, which may lead to innovation are a major source of change. In external or system path-dependence, system wide accumulated competencies as well as interaction structures such as networks or market mechanisms are determining factors. Change can arise from within the system by emerging innovation or from outside by environmental changes (Antonelli 2009).

• Interdependence and feedback effects

Interdependence can be understood as the fact that decisions of actors are directly dependent on the decisions of other economic actors. The generation of global effects by local behaviour (emergence) is one of the main characteristics of complex adaptive systems. However, these global effects may in turn change the interaction between economic agents, thus changing the relationship between different variables. A fact which is usually not incorporated in standard economic models (Anderson 1999). These feedback effects based on interdependencies however, play an important role for instance in the diffusion of innovations. Through interdependence among users the adoption of a technology leads to increasing returns of the adoption. With more users adopting the technology the likelihood of the technology to succeed in competition increases and fosters its dissemination (Antonelli 2009, Durlauf 1997). Technological interdependence and the exchange of knowledge is reliant on different factors such as the proximity across actors in institutional, technological (cognitive), social and
organizational terms (Marrocu et al. 2011). Contrasting to neo-classical models, in which agents interact mainly through markets, interaction in systemic approaches also works through networks. These networks can be found between the agents of a certain sector, within or across regions and nations (Ramlogan et al. 2007).

- Heterogeneity

Innovation can be regarded as the outcome of the interaction between heterogeneous agents, e.g. firms, researchers, entrepreneurs. By cooperation these agents can combine their knowledge which is often complementary and thus can lead to the generation of new knowledge (Antonelli 2010). It is the heterogeneity of agents, their often complementary knowledge and capabilities, stemming from processes of cumulative learning, which makes collaboration interesting, thus leading to the emergence of networks (Sammarra and Biggiero 2008). With a complexity approach to technological change it is possible to model heterogeneous agents, even with bounded rationality rather than perfectly homogenous and rational agents (homo oeconomicus). Axtell (2007) argues, that if one acknowledges that agents act boundedly rational, heterogeneous agents are the logical consequence “as there is one way to be rational but many was to depart from rationality” (Axtell 2007, p. 107).

The idea of bounded rationality – as opposed to ‘Olympian’ or full rationality – is based on Herbert Simon’s (Simon 1957) publication on decision making processes in a search process, in which the decision maker searches for alternatives in a step-wise process, i.e. he does not know from the out-set what the optimal solution would be. He is satisfied once the solution surpasses his aspiration level. The aspiration levels however, are adapted based on the situation. If alternative solutions are easy to be reached, the decision makers lowers his aspiration level and v.v. In the innovation process, agents are confronted with R&D inherent uncertainty, unexpected events internal or external to the system or even mistakes in the decision making process. In this sense, agents are short-sighted since their rationality is bound by a lack of knowledge and foresight due to true uncertainty of the innovation process. This does not mean however, that agents may not be able to learn or react to changing conditions, e.g. by means of innovation (Antonelli and Ferraris 2009), bringing about qualitative change in the economy (see Chapter 2.2). Full rationality on the contrary, would require that the decision maker (or agent) knows all possible solutions from the beginning, i.e. has access to unlimited information, and based on unlimited computational capabilities, can make optimal decisions within a very short time span (Selten 1999).
2.4 Innovation in Knowledge Intensive Industries – A Networks Perspective

As the knowledge base of these industries (like in nanotechnology) shows a high degree of complexity, collaboration between agents and thus networks can help to get access to the very different knowledge areas needed to generate innovations by combining existing or by creating new knowledge. Furthermore, being part of a network helps actors to cope with the high degree of uncertainty of the innovation process, e.g. by setting standards within the network (Hanusch and Pyka 2006). On top of that, innovation networks may also provide access to financial resources, markets or research facilities.

According to Pyka (2002), the formation of networks has three main aspects:

- with networks, the diffusion of knowledge is supported, thus supporting inter-firm learning
- networks bring together firms with very different but complementary knowledge bases, allowing for their exploitation. This is especially important in knowledge intensive industries with a complex knowledge base
- the combination of different fields of knowledge is also a starting point for the generation of new knowledge and innovations, thus networks allow for the exploration of novelties.

Depending on their purpose, innovation networks can have very different forms. Connections may be established between different types of actors in e.g. industry-university networks, pure research networks between universities, or networks between universities, industry and governmental institutions (the so-called ‘Triple-Helix’ (Etzkowitz and Leydesdorff 2000). The links between the actors may also differ, ranging from R&D collaboration, to financial collaborations (such as equity stakes or the provision of venture capital to marketing collaborations (Powell et al. 2002).

Innovation networks show certain characteristics when analysed with SNA methods (see below). These general characteristics (Powell and Grodal 2005) are based on the structure of the network. There are two main ways for capturing and revealing the structure of a network. First, by visualising the network as a graph. The visualisation is based on algorithms, which are usually selected based on the type of data to be analysed. This determines which algorithm is most suitable for revealing the network structure. Second, network statistics can be computed on the level of the entire network, a sub-network or on the level of nodes and links (see methodology section). The structures not only emerge from the interaction between agents or the relation between pieces of knowledge, these structures in turn influence the innovation performance of
In the following, some of the main characteristics of innovation networks are described.

Innovation networks in knowledge intensive industries usually are characterised by a power law degree distribution (Barabási and Albert 1999). This means that a small number of actors has a very high number of connections (hubs of the network) to other actors, whereas the great majority of actors only shows a very low number of connections, i.e. a low degree (Boccaletti et al. 2006). Hubs in these ‘scale free networks’ are said to enable fast and effective knowledge flows between all network partners (Malerba et al. 2006).

In small world networks participants are mainly connected to the neighbours within their cluster but are connected to every other node of the network by only a short path length. A small world graph is defined by larger clustering coefficient of the actual network compared to the clustering coefficient of a random graph with the same number of nodes and average degree (Watts and Strogatz 1998). This enables knowledge to flow quickly and at a high rate (Pyka et al. 2009).

However, in classical transaction theory, networks were considered to be only a temporary phenomenon. With the framework of evolutionary economics, their persistence can be explained by taking the perspective of knowledge creation and diffusion, which underlines the advances of networks for inter-firm learning, exploitation of complementarities, reaping of synergies and exploration of new fields (Pyka 2002b). Networks are thus an emergent phenomenon and may consist of actors or pieces of knowledge. These networks emerge within the innovation system which is analysed. The theory of innovation systems provides – in combination with the theory of evolutionary / neo-Schumpeterian economics, the main body of theoretical foundation of this work. It shall therefore be described in more detail in the following chapter.

2.5 The systems of innovation perspective

In this section, the basic ideas of the SI approach are introduced. An innovation system “can be defined as a group of private firms, public research institutes, and several of the facilitators of innovation, who in interaction promote the creation of one or a number of technological innovations [within a framework of] institutions which promote or facilitate the diffusion or application of these technological innovations” (Beije 1998, p. 256). The term ‘system’, however, is not in a strict sense perfectly appropriate for innovation ‘systems’, as actors may for example chose whether they are part of the system or not. However definitions used in both, the literature of innovation networks and the literature of innovation systems are very close together (Ahrweiler 2010). In the following section, an overview on the systems of innovation (SI) approach will be given:
Before the approaches can be described in more detail, it is important to define the term 'institution' (Korres 2013). Institutions could simply refer to private, semi-public and public organisations (narrow definition). A broader definition of institutions includes laws, social conventions, contracts, traditions as well as the above-mentioned organisations. In other words, they may take very different forms and be specific to a country, region or sector (Malerba 2003). For the remainder of this work, the term 'institution' refers to this broad definition unless otherwise explicitly indicated.

The National Systems of Innovation (NIS) and the Regional Systems of Innovation (RIS) approaches use geographic delineations to characterise the systems. The Sectoral System of Innovation (SSI) approach focuses on certain sectors of the economy, for instance, chemical engineering.

The different SI approaches can be characterized and compared by investigating how they deal with the following six dimensions (Coenen and Díaz López 2010):

- System boundaries
- Actors and networks
- Institutions
- Knowledge
- Dynamics
- Policy implications

Apart from these dimensions, all three SI approaches share certain characteristics. They all focus on innovation and they all place great emphasis on the learning process (Johnson, Edquist and Lundvall, 2003) in which all actors involved (e.g. firms, consumers, universities, public organisations) experience a ‘learning-by-doing’ process or learn from each other by exchanging knowledge. Systems of innovation are always defined as complex systems (Metcalfe and Ramlogan, 2008), stressing their non-linear, systemic, interactive and evolutionary character (Tödtling and Trippl 2012; Uyarra and Flanagan 2013). Furthermore, the performance of all SI approaches is analysed in a similar way, namely through the ex-post, historical analyses of economic or innovative activity and knowledge diffusion (Godin 2006a). Such analyses are holistic and interdisciplinary, bringing together scholars and analysts from various disciplines (Johnson, Edquist and Lundvall 2003) to account for the many, complex interactions in the system.

However, the functions within an innovation system are less clearly defined (see e.g. Bergek and Jacobsson 2003). Some of the most important include the creation of knowledge, competence building or interactive learning though networking. In the SI approach the different forms of learning play a central role and are categorized as innovation, research and development and competence building.
In the following, the three SI approaches will be described in more detail.

2.5.1 The Three Main Systems of Innovation Approaches

2.5.1.1 National Systems of Innovation

The concept of National Systems of Innovation was developed in the 1980s and is mainly associated with three authors: Freeman (1987), Lundvall (1992) and Nelson (1993). The concept provided a new approach to innovation and its governance and stimulation as compared to the more neo-classical, market failure approaches (Soete, Verspagen, and Ter Weel 2010). Adopting a holistic view of innovation rather than focussing on isolated aspects of the process, the NSI concept emphasises the interaction of actors involved in innovation and analyses how these interactions are shaped by social, institutional and political factors (Fagerberg and Verspagen 2009). The approach was remarkably successful in a short period of time and is now being used in academia and policy contexts (Teixeira 2013). It is often used as an analytical framework (Sun and Liu 2010) for studying the differences between countries concerning their production and innovation systems (Álvarez and Marín 2010).

In order to understand the NSI concept, one can start with the work of the three ‘fathers’ of the term, mentioned above, also acknowledging, however, Friedrich List (1841). The first person to use the expression ‘the National System of Innovation’ was Bengt-Ake Lundvall (1992). However, as he and his colleagues would be the first to agree (and as Lundvall himself points out), the idea actually goes back at least to Friedrich List’s conception of ‘The National Systems of Political Economy’ (1841) and this might just as well have been called ‘The National System of Innovation’ (Freeman 1995, p. 5).

Freeman (1987) employed the concept to describe and explain Japan’s innovation performance. He specifically focussed on the interaction between technology, social embeddedness, economic growth and system-enforcing feedback loops (Soete et al. 2010). The emphasis in his work was placed on four elements of the Japanese NSI:

- the role of policy (in particular the role of the Ministry of International Trade and Industry),
- the role of corporate research and development (R&D) in accumulating knowledge and developing advantages from it,
- the role of human capital, the organization of work and the development of related capabilities,

5 Market failure approaches based on neo-classical theories argue that investment in R&D in order to generate innovation is below its optimal level when external effects of knowledge generation interfere (e.g. a third party profiting from the knowledge generated). Policy intervention is then justified if market failure is clearly identified and the measure taken can bring the market closer to its optimal state (Soete et al. 2010).
and finally the role of industrial conglomerates in being able to profit from innovations emerging from developments along the entire industrial value chain. Like Freeman, Lundvall (1992) emphasises the role of interaction for the production and the dissemination of new and valuable knowledge, shifting away from a sectoral view towards a broader view of the national institutional environment. Emphasizing the role of the nation state, Lundvall outlines three major building blocks of an NSI (see Fig. 5). The first building block deals with the sources of innovation and the actions of agents which lead to innovation, such as learning and exploration. The second building block distinguishes between two types of innovation, namely radical and incremental innovation. Finally, non-market institutions form the third building block. For these, Lundvall distinguishes between user-producer interaction as an important form of knowledge exchange and institutions and their uncertainty reduction function. These institutions play a particularly central role in the NSI concept (and in all other SI frameworks).

Fig. 5: National Systems of Innovation building blocks according to Lundvall (1992)

The third main author in the field, Richard Nelson (1993), focuses on the set-up of actors and how and why they collaborate. He is mostly interested in the institutions working in

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6 Patent laws, for instance, reduce the risk of not being able to protect new knowledge, guaranteeing appropriate return on investments, which are necessary to generate the protected knowledge.
the science and technology sector or supporting it, especially universities conducting R&D.

Based on these three major contributions, the NSI approach has been developed further over the past 20 years, and is now considered "one of the most important concepts to emerge in the field of innovation studies" (Martin and Bell 2011, p. 896). The concept is widely used in country strategies for innovation – in both developed and developing countries. The first developing country to utilise the NSI concept in developing its overall innovation strategy was South Africa.\(^7\) Current work draws on Nelson when analysing the institutions of an innovation system and how the system is organized, and on Lundvall when the focus is on knowledge creation and learning. In the latter case, the learning society, which creates knowledge, is considered the most important resource of an innovation system and learning its central mechanism. From this starting point, the notion of the knowledge economy was developed (Godin 2006a). Looking at both streams, five main elements of the concept emerge following the comprehensive overview of the NSI concept by Luc Soete (2012).

![National Systems of Innovation](image)

**Fig. 6: National Systems of Innovation according to Soete (2012)**

Firstly, the sources of innovation are of great importance in NSI. Classical economics approaches to innovation had relied mostly on an analysis of R&D. However, it is not only R&D that is crucial in innovation. Producer-consumer relations (Lundvall 1992)

\(^7\) The NSI became the central organising concept in the White Paper (Kaplan 1999).
provide a source of innovation, as do the purchase and availability of equipment and the training of workers. Thus innovation occurs in production, distribution, and consumption (Godin 2006a).

Secondly, institutions and how they shape the interactions between actors within the system are of central importance. Market and non-market institutions constitute the national innovation system (OECD 1999), providing the framework for governments to implement policies in order to influence the process of innovation (Metcalfe 1995). The importance of institutions can be illustrated by a quote from Warren Buffett, the most successful investor of the 20th century. He said: "If you stick me down in the middle of Bangladesh or Peru, you'll find out how much this talent is going to produce in the wrong kind of soil" (Singer 2009, p. 43). In a country without reliable governance structures, somebody with the same talent who works just as diligently might still end up extremely poor. The importance of institutions must therefore not be underestimated. It is these institutions which are a preferred target of policy intervention at the national level.

Interactive learning is the third element. It emphasizes the importance of continuous learning in order to adapt to changes. This also demonstrates the connection of the NSI to concepts such as human resource management, labour market institutions and learning capacities of firms (Arundel et al. 2007), as well as to absorptive capacities8 (Nooteboom 2000) of firms and the economy as a whole. Interactive learning is also closely connected to the fourth element, which is interaction. Since innovation is considered to take place almost exclusively within interaction, successful systems of innovations are capable of producing an environment of continuous knowledge production, knowledge use and innovation. However, the interaction is mostly coordinated by institutions and thus an institutional environment which leads to inefficient coordination of interactions may cause failure of the whole innovation system.

Finally, social capital (most importantly trust) is considered an important element in the NSI approach. It is argued that, the greater the degree to which institutions in a system are advanced, the more social capital in the form of trust they show. Trust in turn has a positive influence on the rate of innovation since trust reduces the risk that accompanies innovation and especially the risk of financing innovation (Soete et al. 2010). Fig. 4 depicts the connections between the main elements of the NSI approach according to a study by the OECD (1999). It shows how the NSI approach connects to other systems of innovation (see subsequent sections) and shows the factors which are influencing the system (outer ring).

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8 “The ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends” (Cohen and Levinthal 1990, p. 128).
Fig. 7: The National Systems of Innovation Concept (OECD 1999)

- Macroeconomic and regulatory context
- Communication infrastructures
- Education and training system
- Global innovation networks
  - Knowledge generation, diffusion
    - Firms’ capabilities and networks
    - Other research bodies
    - Supporting institutions
  - Science system
- Clusters of industries
- Regional innovation systems
- Product market conditions
- Factor market conditions
- National innovation capacity
- COUNTRY PERFORMANCE
  - Growth, job creation, competitiveness
The NSI approach has found acceptance amongst policy-makers, as it provides a more comprehensive approach with more opportunities for input than is provided by the traditional market failure approach, which includes correction through policy intervention. Thus, the NSI approach was used at a national level, for instance in Sweden and Finland, and at a supra-national level, for instance at the OECD (OECD 1997, OECD 1999).

The more comprehensive nature of the NSI approach has two positive consequences for policy intervention. The use of policy instruments can be justified more broadly, for instance in the case of stimulating university-industry collaborations. In a market-failure approach, this would be justified by the need for public investment when the market fails (e.g. universities), whereas in the NSI approach influencing the distribution of knowledge and increasing the capabilities of firms could serve as an obvious justification. Secondly, as policies are part of the complex, interactive system, policy-makers cannot design the system top-down as was the case with the market failure concept. Unforeseen repercussions of the top-down approach need to be avoided through more evenly based interactions and communications (Soete et al. 2010). In this regard, the NSI approach is more democratic than the traditional approach.

There are, however, a number of shortcomings of the NSI approach. Since the NSI approach (like all SI approaches) is not a formal one, there is no agreement on what has to be taken into account and what needs to be analysed when looking at a national innovation system. Furthermore, the NSI approach, despite having been worked on for more than two decades, still remains 'under-theorized' in terms of a lack of common definitions and terminologies. Based on the fact that the concept evolved around empirical studies of well-developed systems (e.g. Japan), critics argue that the NSI approach is mainly an ex-post analysis framework, which means that developments have already taken place and are later analysed. This approach lacks the possibility of ex-ante system building (Johnson, Edquist, and Lundvall 2003). In other words, if a good system, framework or institution exists, the NSI can draw attention to it and explain why it is good. As such, if one country has developed a good framework, others may be able to learn from it, depending on the degree to which their existing institutions and social practices are similar. Reflecting on Buffett's comment about Bangladesh and Peru, it might be difficult to develop well-functioning innovation institutions based on experiences from, say, Japan or Germany.

A further challenge for the NSI approach can be seen in the increasing innovation activities, which do not require research (Cowan and van de Paal 2000), especially those activities connected to the ICT and internet sector in a globalised economy. These global developments limit the effectiveness of national policies (Soete et al. 2010).
2.5.1.2 Regional Systems of Innovation

The NSI approach assumes homogeneity within countries, but this is not necessarily the case. On many indicators (e.g. economic performance, poverty, R&D investment) areas within countries can differ significantly (see Bavaria versus Saxony-Anhalt in Germany, for instance). As a result, researchers and scholars of innovation systems have developed a regionally-based approach of innovation system thinking, with ‘regions’ usually referring to a geographical area within a country. The research focus in the Regional Systems of Innovation (RSI) concept therefore rests on the relationship between technology, innovation and industrial location (D’Allura et al. 2012). This spatial concentration remains important for innovative activities, despite the argument that modern information and communication technologies would render spatial distances between communication partners unimportant (Asheim and Gertler 2005). Silicon Valley is normally used as the prime example for a region with great innovative potential.

Even though many aspects of the NSI approach can be applied at the regional level, the RSI approach differs decisively from the former (Korres 2013; Korres 2012). The internal organisation of firms, the relationships between firms, the role of the public sector and public policy as well as the institutional set-up of, for example, the financial sector, are amongst the features that can be explored in detail at a regional level. At a national level these aspects could differ considerably.

The RSI approach thus highlights the regional dimension of the production and the exploitation of new knowledge, thereby helping to explain regional differences in innovation capacity and economic strength.

RSIs usually consist of a set of interacting private, semi-private and public organisations, interacting within an institutional framework. This framework supports the generation, exploitation and dissemination of knowledge and thus supports innovative activities at a regional level (Asheim, Coenen, and Svensson-Henning 2003; Cooke 2004; Doloreux 2003). The RSI approach was developed mainly by scholars of geographic economy who were trying to understand the special role of institutions and organisations in the regional concentration of innovative activities (Asheim et al. 2003; Asheim and Gertler 2005). At the same time, other closely connected concepts emerged such as regional clusters (Porter, 1990), industrial districts (e.g. Becattini 2004; Scott 1988), Technopole\(^9\) (e.g. Benko 1991), learning regions (e.g. Florida 1995) and innovative milieu (Maillat 1995; Crevoisier 2004).

\(^9\) A Technopole describes an institutional environment fostering innovation, technology transfer and university/industry collaboration. Universities and private companies are the central players in the Technopole.
There have been several attempts to understand and structure the research conducted under the umbrella of RSI (see for example D’Allura et al. (2012) and Asheim and Gertler (2005)). According to Doloreux and Parto (2005), RSI research focuses on three main dimensions:

- firstly, the interactions between the actors of the innovation system in relation to the exchange of knowledge;
- secondly, the set-up and the role of institutions supporting knowledge exchange and innovation within a region; and
- thirdly, the role of RSI in regional innovation policy-making.

Fig. 8 depicts the concept of RSI, showing the main actors and dimensions and how they interact.

![Regional Innovation System Diagram](image)

2.5.1.2.1 Knowledge exchange through interaction of actors

The first dimension focuses on the generation and exchange of knowledge within the region. Innovation is increasingly based on interactions and knowledge exchange between the various actors involved in the innovation process, such as firms (large and small), customers, research organisations (e.g. universities and research laboratories) and public agencies (e.g. technology transfer centres). Spatial proximity becomes important when one considers the idea that only small parts of innovation-relevant knowledge can be codified and thus shared easily over long distances, whereas the
exchange of tacit knowledge (Polanyi 1966) requires short distances and face-to-face interactions which in turn facilitates learning-by-interacting (Asheim and Gertler 2005). As such, it is clear that the advantage of regional collaborations over national collaborations is the increased possibility for face-to-face interactions. Within the RSI approach, interaction takes place in various forms, but most importantly in the form of organisation-to-organisation interaction within a network, which gives innovation its systemic dimension (Lundvall 1992). The relationships within these networks show some degree of interdependence and – most importantly for the RSI approach – are very often regionally contained. This is especially true for cases in which partners are more specialised and have a more specific knowledge base. Such specialisation is associated with a high degree of tacit knowledge, and thus face-to-face interaction and trust-based relations become increasingly important (Asheim and Gertler 2005). It is the interactive learning in regional contexts and the dissemination of 'sticky' knowledge which make the regional concentration of actors the best environment for an economy which is knowledge- and thus innovation-driven (D’Allura et al. 2012). Given that innovation is an interactive and dynamic process which relies on the learning in networks (Lundvall 2002), it is often argued that being locally embedded is especially important for small- and medium-sized companies (SMEs) (Audretsch and Feldman 1996), and that communication within the networks is susceptible to a distance decay function (Howells 1999).

The strong focus on regional networks and on learning within these networks has also been criticised: Hess (2004) and Grabher (2006) warn of a danger of over-territorialisation and a tendency to neglect the importance of non-local links (to other regional systems, to the national and the global systems), whilst at the same time over-stressing the benefits of proximate relationships. This exposes the danger of lock-ins and a reduction in the capacity of the region to adapt to changes (Grabher 1993).

2.5.1.2.2 The importance of institutions for regional innovation
The second dimension is concerned with the institutional set-up of a region, supporting the creation and dissemination of knowledge. Here, institution again refers to the broader definition, and hence ‘institutions’ include, for instance, laws, regulations, traditions and also governmental organisations. According to Uyarra and Flanagan (2013), the institutional environment in which the different actors are embedded is at the very heart of discussions on inter-firm relationships and thus of the RSI framework. The emphasis on institutions was mainly advanced in economic geography through the ‘institutional

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10 Tacit (un-codified) knowledge is considered ‘sticky’, i.e. regionally bound by the context in which it is used.
Institutions are said to have great impact on firms in terms of how they interact with each other and, most importantly, in terms of how networks between them become established and function (Uyarra and Flanagan 2013). Local innovation networks are supported by these institutions, thereby supporting the firms involved, particularly SMEs (Cooke and Morgan, 1993). Asheim and Gertler (2005) underline the importance of institutions with their definition of RSIs as “institutional infrastructure supporting innovation within the production system of a region” (p. 299). This regionally dense institutional set-up which can often be found in successful RSIs was described by Amin and Thrift (1995) as institutional ‘thickness’.

The institutional set-up is often used to develop typologies of RSI, of which many types can be found in the literature (Tödtling, Lengauer, and Höglinger 2011). One of the most prominent typologies of RSI was suggested by Cooke (2004), distinguishing three types of RSI based on the prevailing type of governance in the system.

In the first type, called grassroots, in which action is initiated predominantly at a local level, financing is provided by local banks; the research has an application and a near-market focus; the specialisation of companies shows a great variety; cooperation between companies is high, and the main coordination mechanism is the market. Important examples can be found in the regions Emilia-Romagna (Italy) and the Silicon Valley (USA) (Fig. 9).

At the other end of the spectrum, one finds the dirigiste type. Here, activities are initiated centrally; funding is provided at the national level; the research is basic and innovation is upstream-oriented; the degree of specialisation is high, and regional cooperation is low and state-coordinated. One prominent example can be found in the Midi-Pyrénées region (France) (Fig. 10).
In between these two types, the integrated RSI depicts multi-level initiatives; funding is provided by various partners; research and innovation is a mix between applied and basic, and one can observe an upstream and downstream orientation. Firms are specialised to a medium degree, and regional cooperation takes place in networks, which are associatively coordinated. Prominent examples can be found in the Steiermark (Austria) (Fig. 11) and Baden-Württemberg (Germany).

Based on the notion of institutional thickness, Tödtling et al. (2011) distinguish between 'thick' RSI, which can often be found in metropolitan areas such as the Vienna region, and 'thin' regions such as can be found in the Salzburg region. Differentiating factors are the number and size of knowledge-generating and knowledge-disseminating organizations (universities, private and public research organisations), the number of firms and the degree of activity within their networks. They argue that clustering in 'thin' regions is lower; firms are less specialised, and the density of research and supporting organizations is low, resulting in an overall lower level of innovative activity and weaker learning preconditions.

The focus on institutions has also been criticised, especially when it is undertaken exclusively. Gertler (2010) points out that, whilst the role of institutions within RSI is of great importance, it remains poorly understood. Often, an a-historic view is taken, ignoring and underestimating the role of the historic context, i.e. the emergence, evolution and disappearance of institutions. The role of institutions is also too often reduced to a list of functions. Even if one has a good list of functions, it would be incorrect to conclude that these functions (such as knowledge production) are the sole raison d’être for the respective institution (Uyarra and Flanagan 2013). Likewise, it is also questionable whether all systems would consist of the same institutions fulfilling the same roles (Cooke 2001), for instance intellectual property rights in one region of one country could be more important to innovators than in another region of a different country. The functions of institutions are often different from the intended ones (Flanagan et al. 2011) or overstated, underestimating the role of agents (Flanagan et al. 2011).

Whilst this second approach to RSI, with its focus on institutions, provides many
important indicators of what works in innovation and what does not, an exclusive focus is not always helpful.

2.5.1.2.3 RSI and innovation policy

The role of policy in the RSI approach is the third important dimension - one can even say that RSI is both a theoretical concept as well as a policy objective (Cooke, Uranga, and Etxebarría 1997). It is the policy level at which the national system exerts huge influence over the regional systems (Korres 2013). One major example of the application of the third dimension of RSI approach can be found in the structural policy of the European Union. Fig. 12 shows the innovative activities of all 250 regions of the EU. Differences are tightly monitored in the long-running Community Innovation Survey (CIS), the results of which are published yearly in the Regional Innovation Scoreboard of the European Commission.\textsuperscript{11}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Fig_12.png}
\caption{Innovation regions of the European Union (European Union 2012)}
\end{figure}

As the map shows, innovative activities are geographically distributed in an uneven manner, both within countries and even more so within the EU. The same is true for networks and how they function and evolve over time. Applying different policy approaches at a regional level within the same country may lead to regions learning from each others’ experiences. Such a regional approach is also capable of bringing policy measures closer to citizens, in accordance with the principle of subsidiarity, and it bridges the gap between the supra-national level of the EU and the regions (Korres 2013).

One major contribution of the RSI concept to the innovation system debates is the idea that there is no single one-size-fits-all policy. Policy instruments should always be context-specific and need to be adapted to the regional circumstances. Policy intervention in the RSI context mostly targets system failures, trying to facilitate the effective functioning of complex interactions between the various actors in the regional system. Policies at the regional level may target the regional set-up at various points, for instance they may affect all actors of a region or just firms or even single persons. The measures implemented can help companies to overcome a shortage of competencies; they can introduce hard institutions such as laws, or tackle soft institutions such as the willingness to take risks. They may even intervene at the network level, helping to overcome lock-in effects (e.g. where two partners have been working with each other in stagnation to the exclusion of others), or helping to initiate more collaborative activities in order to assist companies in finding sources of complementary knowledge (Asheim et al. 2013).

Criticisms of the RSI approach's focus on policy mainly target the risk of normative thinking and the danger of overestimating the capabilities of regional innovation policies. When a normative view is adopted, there is a danger that one may draw implications from stylised constructs, often drawn from empirical case studies, and try to reproduce them. This line of reasoning would ignore the importance of bottom-up processes, initial conditions and the context- and time-specific notion of regional systems. Policy-makers may be tempted by the RSI approach to act in disregard of these specific features, expecting that they can act effectively independent of the context and overestimating the role of innovation for regional development (Uyarra and Flanagan 2013).

2.5.1.3 Sectoral / Technological Innovation Systems

Unlike the innovation system approaches described in the previous sections, which both rely on a spatial dimension to define their boundaries, the sectoral as well as the technological innovation system approaches adopt a certain technology (spanning multiple sectors) or the sector in which it is used (including various technologies) as their system boundary. The notion that particular sectors have different technological
trajectories was first spelt out by Dick Pavitt (1984). Pavitt developed a taxonomy according to the sources of technology, the requirements of users and the appropriability regime. The taxonomy was four-fold:

- Supplier-dominated sectors – mostly traditional manufactures such as textiles and agriculture, which rely on outside sources for innovation
- Scale-intensive large firms producing basic material and consumer durables such as autos, white goods; sources of innovation are both internal and external to the firm
- Specialised suppliers – producing technology to be sold to other firms
- Science-based ‘high tech’ goods which rely on in-house and publicly funded research eg. pharmaceuticals

The concept of sectoral innovation systems was further developed by Malerba (2002), whereas the development of the technological approach can be traced back to Carlsson and Stankiewicz (1991). Both concepts are, compared to the NSI and the RSI approaches, more weakly developed and have a smaller overall impact. In both approaches links between firms and other organisations are portrayed as occurring as a result of the technological interdependence of their knowledge (Chang and Chen 2004).\textsuperscript{12} Fig. 13 depicts the relation between national (NSI), sectoral (SSI) and technological (here TS) systems of innovation.

\textsuperscript{12} For a detailed discussion about the communalities of and differences between the two concepts see Coenen and Díaz López (2010).
Carlsson and Stankiewicz (1991) define the Technological System as networks of agents, who act in a specific technology area within which a particular institutional set-up exists. They conceptualize their approach with four main elements:

- economic competence, which describes the firm's competencies,
- clusters and networks, which are important because innovation happens in interaction and networks are an alternative governing instrument,
- institutions, which act as 'signposts' and provide stability for firms (Coenen and Díaz López 2010), and finally
- development blocks, which create tension of alternating strength, thereby creating development potential, i.e. areas of technological development which relate to each other in various ways and induce innovation by evolving in various ways.

The SSI concept of Malerba (2003) consists of three building blocks, which are the knowledge and technological domain, the actors and networks, and the institutions.

- The knowledge and technological domain is the domain in which the boundaries of the system are defined, and these are unlike the boundaries in the NSI/RSI approach dynamic and thus are part of the analysis. System boundaries are also defined by links and complementarities among artefacts (e.g. a product or a technology) and activities, and are either static or dynamic.
• The actors and networks within a sector are heterogeneous in type and include, for instance, individuals, firms, and semi-public or public organisations. Learning processes, behaviour, objectives and competencies are connected via market and non-market relationships. Firms, however, are at the centre of the concept due to their primary influence on innovation, rendering other organisations as secondary (Coenen and Díaz López 2010).

• The notion of heterogeneity of actors also applies to consumers, i.e. demand is also structured and influenced by consumer interaction, competencies and institutions. Consequently, relationships and networks are sector-specific, according to the sectoral knowledge base, learning processes, basic technologies, links and complementarities.

As in all SI approaches, institutions also play a major role in the SSI concept and shape the actions and interactions of agents in the system and help to guide the behaviour of agents in a certain direction (Coenen and Díaz López, 2010). However, national institutions affect the sectors differently. Regulations such as property rights and patenting rules may favour one sector (e.g. the pharmaceutical industry) and hamper another (e.g. the food industry). These effects may also vary across countries. For instance, European pharmaceutical companies benefit from the changes brought about by the TRIPS\textsuperscript{13} regime, whilst Indian generic drug manufacturers are badly affected by TRIPS. The influences of national institutions on sectoral systems and vice versa are mutual, with a very important industry sector possibly shaping national institutions. Sectoral systems are also prone to change which may be caused by the technology and learning regime in the sector, and by the patterns of innovation. A change in the knowledge base may lead to consolidation within the sector if a new dominant design becomes established, or may cause major changes in the industrial set-up if new competencies are required. The iPhone would be an example of a dominant design. Another source of change is the structure of consumer demand, which may cause new firms to enter the system, possibly changing it considerably. Overall, these dynamics are of a co-evolutionary nature, evoking change at the levels of technology, knowledge, actors and institutions.

Both the technological and the sectoral concepts of innovation can be criticized on various levels, beginning with the boundary setting. The SSI approach is characterized by – as stated above – dynamic boundaries mainly based on existing products, which

\textsuperscript{13} The Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) is an international agreement negotiated through the World Trade Organization (WTO), which applies minimum standards of patent protection globally.
may cause problems when new products emerge. The understanding of institutions in both approaches lacks a system perspective, especially when compared to the spatial systems of innovation approaches. The knowledge and learning perspective in the SSI/TSI concept is biased towards technological learning, whereas social learning is usually not sufficiently considered. The SSI approach has also been criticized for its inability to account for the emergence of new technologies and sectors and for its focus on incremental changes. At the level of concept validation the TSI approach depends upon purposefully designed data sets, in contrast to the SSI approach, which can draw from existing datasets structured according to the NACE\textsuperscript{14} nomenclature (Coenen and Díaz López 2010).

2.6 General Purpose Technologies

2.6.1 The concept of GPTs

The concept of General purpose technologies (GPTs) such as information technology and nanotechnology show, due to their broad applicability, a range of effects on the knowledge landscape of economies, distinguishing them from other, more 'standard' technologies. Despite these effects, research on GPTs is not as prominent as it could be expected based on the importance of GPTs.

The term general purpose technology was coined by Bresnahan and Trajtenberg (1995) who define GPTs as 'characterized by pervasiveness, inherent potential for technical improvements and 'innovational complementaries'. ' (Bresnahan and Trajtenberg, 1995, p. 83). GPTs are said to play a major role in economic growth. By incorporating them in economic models it is possible to explain growth endogenously and provide an integrated model of growth and business cycles (Bresnahan and Trajtenberg 1995). In literature, the term 'enabling technologies' is often used similarly and refers to the combinational character of GPTs: combined with others technologies of the application sectors (AS), the emergence of GPTs spurs a wave of innovations in the sector in which the GPT is applied (Bresnahan 2010). There are, however, also feedback effects as GPTs are applied, as outlined below:

The main characteristics of GPTs according to Teichert (2012) are shown in Fig. 14.

2.6.1.1 Pervasiveness of GPTs:

Bresnahan and Trajtenberg (1995) describe the wide spread use of a technology in various application sectors as the first characteristic of a GPT. Helpman and Trajtenberg

\textsuperscript{14} Statistical classification framework developed by the EU which allows the classification of economic activity (e.g. the number of firms) in sectors, thus making statistics comparable.
(1998, p. 85) add that GPTs are characterised: “ [...] by their pervasiveness in that they are used as inputs by a wide and ever expanding range of sectors in the economy.” Teichert (2012) argues, that the wide applicability of GPTs is the prerequisite of pervasiveness, which is in line with the argumentation of Lipsey et al. (1998) who state that a GPT only becomes pervasive once its improving effect on products or processes is acknowledged. Furthermore, the authors distinguish between real GPTs and near-GPTs such as ‘machinery’ – which has many applications but is too expensive for being pervasive – or the electric light bulb – which is pervasive but has only one use. The pervasive character of GPTs may even have consequences for the financial sector, since a consequence could be that technological changes induced by GPTs causing systemic and non-diversifiable risk (Hsu and Yang 2015).

Pervasiveness is measured with different indicators and levels: Jovanovic and Rousseau (2005) measure pervasiveness by adoption rates at the aggregate level of an economy, as well as at the level of individual sectors, and households. For two technologies, electricity and IT, the adoption rates are calculated: electricity adoption is measured by the total share of horsepower generated by electricity as opposed to steam engines. The adoption rate of IT is measured by the share of capital stock invested in IT. At sectoral level, the share of electrified horsepower across various sectors and the share of IT investments in capital stock respectively, is measured across sectors. At the household level, Jovanovic and Rousseau, measure the share of electrified households. Their analysis reveals the characteristic S-curve shaped pattern of adoption of new technologies.

Teichert (2012) outlines the indicators diffusion of GPT patents in various patent portfolios, measured by relative share in these patent portfolios. With the generality index (see also e.g. Hall and Trajtenberg 2004) and the technological coherence index, two more measures are outlined, with the latter being a weighted and more sophisticated (Teichert 2012) measure for generality. At the core of both indices is the idea that the more diverse the technology areas are that cite a patent, the more general is its applicability and thus pervasiveness. In Chapter 5.4 the coherence indicator is applied to the knowledge level of the SKIN model.

2.6.1.2 Scope for on-going technological improvement

The second main characteristic of a GPT is its ability to improve further, and experience a wide scope of improvements and elaboration in its own technological sector (Cantner and Vannuccini 2012). This characteristic is necessary since without it, the dual inducement process between the GPT and the application sectors (Fig. 14: GPT characteristics) could not be established: by its application in one sector, the GPT gets
improved, thereby widening its applicability in other sectors, which in turn accelerates the improvement and the attractiveness for further investment (Lipsey et al. 1998). A good example can be found in the information and communication technology, in which the marginal costs are often very low (e.g. in software) and in which an endless stream of highly customisable innovations can be found (Park et al. 2007). In nanotechnology, similar traits can be identified with the reduction of size, lower cost, and greater complexity (Youtie et al. 2007).

In the literature, several different indicators for measuring the scope for ongoing technological improvement can be found: Jovanovic and Rousseau (2005) use the decline in price of the technology or its increase in quality as measure for on-going improvement. Palmberg and Nikulainen (2006) argue that the accelerating growth of nanotechnology-inventions underlines the ongoing technological improvement, while Schultz and Joutz (2010) are facilitating patent citations for this purpose.

2.6.1.3 Innovation spawning in application sectors

According to Jovanovic and Rousseau (2005) a GPT ‘should make it easier to invent new products or processes’ (p. 1185). Schmitt (2015) describes innovation spawning as a ‘Strong and lasting impact on product and process innovation in a broad range of uses and/or application sectors’ (p. 31). This characteristic must not be confounded with ‘innovational complementaries’, even though at a first glance they seem to be interchangeable. Innovational spawning aims at the idea that innovations down the value chain are enabled or triggered by the GPT, in combination with technological dynamism, innovational spawning propels the development of complementaries (Teichert 2012).

The nanotechnology value chain as described in 5.4 can be considered a good example for innovational spawning: nanotechnology triggers innovations from the development of nano raw materials, over carbon-nanotubes to coatings enabled with carbon-nanotubes and applied on various products (Forfás 2010).

In Chapters 5.4 and 5.5 innovational spawning is modelled in line with Teichert (2012) by the existence of value chains enhanced by GPT knowledge.

The spawning of innovations is measured in the literature based on patents (increasing share of patents or citations form a non-GPT patent to a GPT patent) (e.g. Shea et al. 2011), or based on technological classes. For the latter, if the number of classes citing the GPT grows, this can be interpreted as innovation spawning (Hall and Trajtenberg 2006), yet, this is not restricted to technology classes in patents but can also be applied e.g. to publications (Teichert 2012).
2.6.1.4 Innovational complementaries

This characteristic also goes back to the original definition by Bresnahan and Trajtenberg (1995) who distinguish between horizontal and vertical complementaries. Vertical complementaries can be found between the GPT sector and the application sectors. As stated in Chapter 1, an example could be the microchip (enabled by nanotechnology) on the one hand, and the ability to manipulate living cells (also enabled by nanotechnology). Horizontal complementaries can be found in the connection of both: the combination of a microchip and a living cell, resulting in a living electronic sensor.

Other authors describe the consequences of GPTs for downstream industries: Vuijsteke et al. (2007) state that R&D productivity increases as a consequence of the GPT, hence R&D investment increases in those sectors, where GPTs are introduced.

Measuring innovational complementaries in empirical data seems to be problematic. The only indicator to be found in the literature is developed by Teichert (2012) with the IC (innovational complementarity) index: ‘Put differently, this indicator hence calculates the share of patents that triggers a mutual innovation process from the original technology to a technology from another field back to the original technology (p. 118).

Due to its perceived lack of relevance and missing alternatives, a further consideration of this indicator is not taken into consideration.

Fig. 14: GPT characteristics

According to Teichert (2012)

2.6.1.5 Knowledge mergence

A relatively new line for developing GPT measures was proposed by (Teichert 2012), drawing on the multiple application possibilities. Teichert develops two measures in order to reveal the knowledge merging character of GPTs. With measuring the generality of backward citations, arguing that the more diverse the technology areas are from which
the GPT draws, the more merging it can be regarded. With backward coherence, which can be basically regarded as a weighted generality measure, a second is applied. This characteristic is relatively new in the theory of GPTs, however, it seems to be a promising path for further investigation. In chapter 5.4 with the application of the modularity measure an SNA approach to this characteristic of GPTs is taken.

2.6.2 Literature on GPTs

According to Schiess (2011) the literature on GPTs can be classified in two main strands: The first strand mainly deals with the invention of GPTs, the second strand with their diffusion. Models focussing on the invention of GPTs can be further divided into models which emphasize the connection between R&D efforts and growth triggered by the emergence of one or more GPTs, and models which underline the need for complementary innovations in order to make use of the GPTs. Both strands rather focus on the explanation of long-term growth whereas lifecycles (of both, the GPT as well as the application technologies) are not taken into account. In the complementary-focussed models the diffusion of a GPT is determined significantly by the complexity of the complementaries to be developed for the application of the technology (Bresnahan 2010) and might differ from AS to AS.

Literature on the diffusion of GPTs either deals with domestic diffusion or sectoral diffusion characteristics, thereby focussing on the s-curve shaped pattern of diffusion. Diffusion is measured on various levels, such as households or industries (Jovanovic and Rousseau 2005) or in multiple sectors at the same time using a classical or evolutionary framework (Strohmaier and Rainer 2013; Rainer and Strohmaier 2014). Other models apply a North/South framework, emphasising relative productivity differences. Most of these models mainly try to explain the productivity paradox – the empirical fact that productivity slows down in the early phase of the advent of a new GPT. This phenomenon was first described by Robert Solow, referring to the developments after the introduction of computers in the economy, which did not lead to higher productivity. However, several years after the introduction productivity and growth rates rose again. The same effects could be identified for other GPTs. These models are therefore attempting to explain more short-term waves of growth (as first described by Konratiejff) by the emergence of one or more GPTs (Bresnahan, 2010; Schiess, 2011). For example Aghion and Howitt (1998) are able to replicate the s-shaped curve of diffusion. Thereby they are able explain the productivity paradox as many other diffusion models which are taking into account time lags and critical masses of users of a GPT needed to unfold a GPT’s full effect (Schiess 2011). However, these models are ignoring the importance of networks and different network settings within the application sectors,
the effect a GPT has on the industry architecture of a sector, and possible backward, forward and spill-over effects. With my work I try to contribute to the literature by modelling the diffusion of the GPTs within different application sector networks from a knowledge perspective and take into account the various interdependencies.

The models not only differ in endogenous emergence of the GPT or an exogenous GPT shock, but also in how GPTs are replaced. Some use Schumpeterian competition, modelling new GPT as replacing the old one and never allowing for more than one GPT being used at the same time. Others allow for more than one GPT affecting the application sectors at the same time (van Zon, Fortune, and Kronenberg 2003; Schiess, 2011).

Another important model from which ideas can be drawn is the GPT model of Carlaw and Lipsey (2006). It focuses on the invention of GPTs and the importance of R&D efforts. The authors model three sectors (fundamental research, applied research, consumer goods), each of which has its specific production function. Continuous growth in the model is only possible through the repeated introduction of new GPTs. Uncertainty exists concerning the effects of R&D activities on the sequence of GPT arrivals and effect they unfold. However, the model also has some shortcomings: it keeps the emergence of GPTs exogenous, it does not model the different effects of the GPT on different sectors and it does not model the emergence and diffusion of the new GPT knowledge within the system. With a network approach in which innovations emerge from the collaboration of actors by combining their knowledge, GPT emergence could be endogenized. Growth waves caused by industry life cycles are an important stylised fact, which our model has to be able to replicate. In the model AS industries should show a ‘standard’ lifecycle, unless they are recombined with the knowledge of a new GPT. This should then lead to a revival of the AS technology, causing wave-like growth at an aggregate level.
3 Design of Research and Methodology

Based on the theoretical foundations outlined in the previous chapter, this chapter aims at developing the conceptual framework for this thesis, followed by a section outlining the detailed research questions based on the research problem and the theoretical framework. The chapter concludes with the introduction of the main research methods and the SKIN model, which is central to the publication in Chapter 5.4.

3.1 Conceptual Framework

The research of this thesis is based on the notion of innovations emerging in complex social systems. General purpose technologies and thus nanotechnology as such, can be approached using the notion of complex systems and applying the methodologies and tools therein.

As shown in Chapter 2, the linear model is neither close to reality concerning the way innovation is generated nor is it capable of capturing central aspects of knowledge generation, diffusion and commercialisation: knowledge is mostly generated by collaboration in networks, its generation and diffusion is subject to path-dependencies and feedback loops. The commercialisation of knowledge in innovations takes place under true uncertainty. By means of evolutionary economics these traits are not only captured but the focus of research.

Furthermore, the evolutionary framework understands the importance of heterogeneity, which is represented in the different knowledge bases, behaviours or sizes of actors, such as firms or research organisations. By taking the view of evolutionary economics, other aspects such as path-dependencies, and lock-in effects can be taken into account. Introducing neo-Schumpeterian ideas like the central role of innovation as well as entrepreneurial activity to evolutionary economics enriches the theoretical basis decisively in changing from the ‘artefact dimension’ of innovation in neo-classical approaches to the ‘process dimension’ (Hanusch and Pyka 2010).

By taking a complexity perspective the generation of knowledge, non-linearities e.g. in the exchange of knowledge (Ahrweiler et al. 2016) as well as network structures within technology sectors, regions or nations can be understood as emergent phenomena of micro-level processes (Martin and Sunley 2007). Knowledge itself can also be regarded as being heterogeneous and complex. The combination of complexity and uncertainty has to be taken into account by an analytical concept if it is to be useful for policy modelling and advice (Ahrweiler et al. 2016).

Using the SI approach helps to frame the research and to define the important actors, institutions, relations and boundaries. For the purpose of this thesis, a national
perspective is taken for the empirical research in Publication 1, with an emphasis on nanotechnology. The GPT characteristics of nanotechnology as described in Chapter 2.5, especially its wide applicability may eventually lead to a high degree of congruence between the national and the sectoral (namely nanotechnology) system. However, as described in Chapter 2.4, the main object of research, e.g. actors or institutions, may still be different.

With the combination of the evolutionary theory of innovation and aspects of complexity in innovation, framed by the SI approach, it is possible to capture the central features of the innovation process. The SI approach is the most favoured framework for describing, analysing, and understanding the process of innovation at various levels, and how it can be influenced by policy measures. To policy makers, innovation and innovation systems are becoming increasingly interesting for achieving economic and social goals. The attractiveness of the concept to policy-makers is based on the fact that SI approaches can draw attention to weaknesses in the system (Soete, Verspagen and Ter Weel 2010; p. 1162) and that scholars do not ignore the policy context.

The special characteristics of GPTs and their underlying, widely applicable knowledge have made them a field of study on their own. So far, the huge majority of GPT models has approached either their generation or diffusion from a mostly neo-classical perspective. With this thesis, an attempt shall be made to show that GPTs can be also approached from a knowledge perspective. It is shown that nanotechnology as a representative of GPTs is connected to many different technological areas. This additional degree of complexity may justify a separate set of policy measures for GPTs. Implications for policy-makers from the SI approach in combination with GPT aspects are manifold. The variables associated with success of policy intervention may be different, requiring a good understanding of the co-evolutionary processes within any technology sector in which the GPT is applied and the GPT sector as such. If policy interventions are over- or under specified or are being enacted at various spatial or technological levels, they may have drastically different impacts across sectors. For instance, policy measures that aim to foster network activities may not cause any effects or even negative effects in some sectors. As a result, a technology and sector specific analysis is required in order to identify how the institutional configuration may evolve based on the policy intervention.

With the methods of computational social sciences such as computer simulations with ABM tools, emergency and agency (e.g. adaptive behaviour of agents) as central aspects of knowledge creation and innovation can be captured. In ABMs network structures may emerge with the simulation and thus connections between agent behaviour and emergent phenomena at the meso and macro-level can be discovered,
explained, and even forecasted. By applying SNA methods, it is possible to assess the network dimension of innovation networks and networks of knowledge and to provide data for validation and calibration of simulation models.

In order to investigate the relations between these actors, to explore why and how innovation is happening in these networks and which structures and processes are connected to the innovation process, a new approach has to be taken. By the use of social network analysis (SNA) methods and agent based modelling (ABM), innovation processes and their impact on different sectors can be modelled, simulated and thereby better understood (cf. Ahrweiler 2010). In Chapters 3.3 to 3.5 a more detailed description of these methods and of the SKIN modelling example of complex innovation networks is given.

### 3.2 Research Questions

Designing sound research and innovation policies requires a proper understanding of the innovation system which is to be influenced. The broad applicability of nanotechnology, and GPTs in general, is expected to exert a great impact on research and innovation activities. This could imply two alternative structures: either, certain areas of nanotechnology are only applicable in a distinct and well-defined application sector. As a result, nanotechnology is being combined with many other technologies, but connections between the application technologies are not being established through nanotechnology. Alternatively, the same piece of nanotechnology can be applied in several areas. All the application areas would then be connected via the respective piece of nanotechnology.

In this case, connections between nanotechnology and other technologies should be found in networks reflecting these technologies. As a representation of technologies and the knowledge incorporated in them, a patent network study is conducted in Publication 1, assessing the following questions:

- **Q1:** Is nanotechnology connecting previously unconnected areas?
- **Q2:** How can these structures be measured and visualized (for later model validation)?

A strong connecting effect of nanotechnology would entail consequences for policy design: cross-fertilisation, feedback-effects and interdependencies would play a greater role in this case. Policy measures would have to account for these connections in order to develop efficient policy measures.
The aim of a majority of policy measures is the support of R&I in order to foster economic growth via innovation activities. In recent years, alternative policy goals have been given more attention, such as the inclusion of the poor, the slowing down of climate change or public health issues. One of the most recent examples is the normative concept of responsible research and innovation, aiming at designing policies, which solve a broader range of societal problems. The next research question is therefore aimed at the future value of modelling policies for when answering this type of questions becomes increasingly important:

**Q3: Can the descriptive SI framework be used to integrate normative questions which arise from the emergence of nanotechnology?**

It is demonstrated how the SI approach and normative research goals can be combined. Based on the SI approach, normative policy questions can be evaluated using indicators e.g. based on the size of innovation networks or the diversity of the actors included. The SI framework in its combination outlined in the previous section should therefore be well-equipped also for supporting future policy makers trying to pursue normative goals.

In order to capture the aspects of heterogeneous knowledge, interacting agents and feedback-effects e.g. from market interaction, a modelling exercise is conducted. The goal is to identify a way of knowledge representation which is capable of showing characteristics of complexity as outlined in the previous section.

For eventually being able to simulate policy scenarios and evaluate policy measures, it is important to show whether an ABM simulating the complex behaviour of knowledge is suitable for policy modelling:

**Q4: How can knowledge be modelled in an agent-based simulation in order to show complex behaviour?**

**Q5: Is ABM a suitable modelling approach for developing policy questions and eventually evaluate them?**

For capturing even more complex characteristics of knowledge, most importantly the relations and the relation dynamics between pieces of knowledge, with the SKIN platform a different (Simulation Knowledge Dynamics in Innovation Networks) ABM is selected. With the SKIN model, it is possible to simulate not only networks between agents active in the innovation process, but also networks of knowledge. The results can be validated against the findings of the empirical study in Chapter 5.1. In order to determine whether
the SKIN model is also already suitable for simulating the emergence and/or the diffusion of GPTs, the next questions aim in that direction:

**Q6: What are the indicators needed to identify GPTs in the SKIN model?**

**Q7: Do GPTs already emerge or disseminate within the SKIN model?**

The work concludes with a summary of the results in chapter five, developing policy implications considering both, the results of the respective publications and the entire study as a whole.

### 3.3 Social Network Analysis in Innovation Research

Analysing network structures and dynamics in innovation research with SNA methods has gained much interest in recent years (Pyka and Scharnhorst 2009). In numerous analyses such as co-authorship networks between scientists (Barabási et al. 2008), collaboration on EU Framework Programmes (Roediger-Schluga and Barber 2007), university industry collaboration networks based on co-patenting (Ma and Liu 2010), co-publication (Olmeda-Gómez et al. 2008) or networks between biotech-companies and venture-capitalists (Powell et al. 2002), SNA methods have helped to assess the structures and dynamics of collaboration networks.

For assessing the structure and dynamics of the relations between entities, network analysis provides several measures on the level of nodes and links.

On node level (which may represent firms, universities, units of knowledge), network measures help to reveal – amongst others – the position of a certain node within the network (e.g. betweenness centrality, closeness centrality), or the number of connections to other nodes (e.g. degree centrality). Each of these measures can help to assign certain attributes to a node: betweenness centrality gives the number of all shortest paths between any two nodes (vertices) in the network running through the respective node. This measure may help to assess the probability that information disseminating through the network passes through the respective node.

Analysing the network regarding the structure of its connections between the nodes helps to reveal the characteristics either of the entire network or a sub-set of it. With the relation between all links in a network to all possible links in a network, network density is measured. The more dense a network is, the quicker information will disseminate. Cliquishnes (for smaller networks) and modularity (for very large networks) are measures used to reveal how much a network is divided into sub-networks. Within these sub-networks, or cliques, nodes are densely connected. Between the sub-networks only sparse connections exist. Applied to innovation research, these cliques may represent
researchers, working together on a certain project, firms operating in the same or similar sectors, or pieces of knowledge being closely related technologically.

Network dynamics and the performance of networks can be understood through the use of robustness, efficiency or effectiveness measures (Coulon 2005). The examination of the diffusion of innovations within a network can be seen as one of the main applications of network efficiency measures (Valente 1999). With SNA methods it is not only possible to explain at which rate innovations diffuse or the sequence of adoption within the network. It is also possible to explain the differences as to why some innovations diffuse more rapidly than others and why some innovations are setting standards, whereas others do not (Abrahamson and Rosenkopf 1997).

Knowledge dissemination, especially the diffusion of tacit knowledge is at the centre of Cowan’s (2004) work. Here, face-to-face communication is essential for disseminating of this kind of knowledge. Hence the role of geographic distance and ‘social distance’, both plays a major role and this can be analysed with SNA. Also, knowledge not only can be analysed as flowing through the network, knowledge itself can be represented as a network (Saviotti 2009).

Apart from network measures, SNA also provides strong visualization methods for social networks. Depending on the purpose of the study, graphs may include different actors as nodes and different relational types as edges between the nodes. Especially for small graphs, a simple optical inspection may already provide valuable insights in the structure and functioning of the network (Barber and Roediger-Schluga 2006).

However, SNA has been ‘just’ a static analytical tool. Network measures and graphs only provide snapshots of the current network states but do neither explain what ‘happens between the states’ (Ahrweiler 2010, p. 6) nor why or how innovation or knowledge is flowing through the network (Ahrweiler 2010). To allow for these questions to be tackled, SNA has to be combined with a theory of agency or behaviour (Coulon 2005).

3.4 Agent-Based Modelling

Agent-based models are computerized simulations in which heterogeneous agents are acting autonomously. These agents react to their environment, the decisions of other agents and, since they may be capable of learning, to their own past actions. Decisions are made based on a predefined set of rules which may include a certain degree of randomness. Agents are not only taking their decisions independently, they may also take states and (future) decisions of other agents into account (Bonabeau, 2002, Gilbert, 2008).

Modelling agents at the micro-level may provide insights and help to understand how their behaviour results in phenomena at the meso or macro level (Squazzoni and Boero
These emergent phenomena can be network structures between agents. Thus, complex patterns like the emergence of certain structures at the meso- and macro-level can already be modelled with a very simple set of relationships between the actors (Bonabeau, 2002, Axelrod and Tesfatsion, 2006). ABM can be seen as providing a bridge between micro- and macro-level classifications (Saam and Harrer 1999) and shows how simple interaction rules at micro level can generate widely observed macro-level patterns, e.g. the diffusion of knowledge, the emergence of innovation, path-dependencies and dynamic returns (Macy and Willer 2002, Pyka and Scharnhorst 2009). These striking features of ABM are accompanied by a couple of issues that ABM has to deal with. First, there is a vast range of agent-based models tackling a large number of issues. This is in contrast to neo-classical economics, where a small number of models are applied to several issues, thus limiting their specificity. Second, ABMs are often not comparable as they are based on very different theoretical frameworks. Even if comparability is possible, models are rarely viewed in comparison but rather are viewed in isolation. This is connected to the third issue, the problem of no existing construction standards which could lead to greater comparability. The last issue is connected to the methodology of SNA, the generation of empirical data (Windrum et al. 2007) and its connection to model building and simulation. There is a discussion on fundamental questions, whether empirical data should be used at all to validate a model or if a simple reproduction of stylized facts can be a sufficient validation method. Other questions arise, e.g. about the parameters which should be implemented and replicated in the model. Windrum et al. (2007) identify six major methodological issues in the empirical validation of simulation models. With the Indirect Calibration Approach, the Werker-Brenner approach (Werker and Brenner 2004) and the history friendly approach (Malerba et al. 1999), Windrum et al. (2007) give three alternatives of how to tackle these issues.

According to Dawid (2006) there are several reasons why ABM is helpful for understanding and explaining innovation processes – especially compared to classical ways of analysis: first, equilibrium models are not capable of explaining many empirical findings of innovation processes whereas they can be modelled and emerge in agent-based models. Second, the assumption of one representative agent which is fully rational does not hold for several reasons: i) innovation is a dynamic process, ii) knowledge, as an essential ingredient of innovation spreads spatially within the innovation network, iii) innovation is a process with a high degree of uncertainty involved, iv) heterogeneous knowledge bases of actors involved are seen as a prerequisite of innovation (Dawid 2006). As path dependency, thus learning and continuous adaption to experiences play a major role in the analysis of e.g. innovation networks, systems analysis by
mathematical means is “very limited in its ability to derive the dynamic consequences. In this case, ABM might be the only practical method of analysis.” (Axelrod and Tesfatsion 2006, p. 1649).

When technological change, triggered by innovation is considered, this dynamic search process is decentralized and characterized by high uncertainty. This search for new products and processes is conducted by many actors in parallel and interlinked through market and non-market processes (Dawid 2006). Through market success or failure, actors receive feedback on their direction of innovation. This in turn leads to company survival or failure, thus shaping the industry.

This very theoretical approach to innovation processes and their influence on industrial systems already shows that a micro-founded model based on interacting actors can capture the effects of innovation on industrial structures. Therefore, ABM is a very promising tool to simulate and thus to understand the processes shaping innovation networks, or, as Dawid (2006) puts it, “The modelling of the dynamic interaction between individuals who might be heterogeneous in several dimensions and whose decisions are determined by evolving decision rules can be readily realized ACE [ABM] models.” The recognition of the complex character of innovation systems and networks made classical economic theories of equilibria and rationality obsolete for the analysis of innovation processes (Squazzoni and Boero 2010).

Being fully aware of the problem of calibration and validation and the question of the actual technical solution to bring empirical data into the simulation model (developing a ‘middleware’ (Ahrweiler 2010)) ABM is nonetheless a very promising tool to simulate and thus to understand the processes shaping innovation networks’. Thus, a micro-founded model based on interacting actors should be able to capture the effects of innovation on industrial structures. In the following section, an agent based model called the SKIN model, will be introduced which could be adapted.

### 3.5 The SKIN Model

The ABM model SKIN (Pyka et al. 2007) captures the dynamics of knowledge emergence and diffusion as well as the networking aspect of innovative behaviour. One main application for the SKIN model is policy modelling where it has already seen numerous applications (e.g. Ahrweiler et al. 2012; Ahrweiler et al. 2016). Agency and knowledge are at the core of the simulation model, in which firms (the agents) are producers, exchange knowledge, do research and collaborate. Knowledge is converted into products, it is altered by research and exchanged by collaboration. The main components are outlined in more detail below (for further details see e.g. Pyka et al.
The SKIN model is introduced here as it is the foundation for chapters 5.4 and 5.5.

3.5.1 Agents

Agents in the model represent firms, which are acting and interacting with each other in various ways, thereby leading to the emergence of innovations and network structures. (Ahrweiler et al. 2004). Firms can either produce a product solely on their own knowledge, in bilateral collaboration, sharing their knowledge with one other firm or in a network, in which many other firms combine their kenes. In order to find a fitting partner, a firm can pursue two different strategies. Either a partner which is technologically not too distant from the firms own knowledge base is chosen (conservative strategy), or a partner which is highly distant is chosen (aggressive strategy). Distance in technology is measured by the difference between the capability shown to potential partners for this purpose.

If collaboration is established, firms jointly produce a product, share the profit and parts of the kenes they have brought into the joint product. By this process, firms can learn from other firms by collaboration (double loop learning). However, collaboration as well as research (see Chapter 3.5.2) comes at a cost: firms running out of funds exit the system and new firms enter the system randomly. If a firm is very successful in selling its products a spin-off enters the market inheriting parts of the knowledge of the parent company.

At the firm level, through collaboration innovation networks between firms emerge. It is in these networks that knowledge is shared and disseminated throughout the system: the knowledge dynamics. Networks between firms are measured and statistically analysed e.g. based on their density, degree distribution or clustering coefficient. Based on these statics, validation and calibration of the model are possible.

3.5.2 Knowledge and products.

The so called kenes in the model represent the knowledge database of an agent (see Fig. 15). Kenes consist of three dimensions: capabilities, abilities and expertise. The capability dimension represents a technology or technology area, defined as integers. Supposedly, a firm possesses the kene examples 1, 2 and 3 in its set of kenes. These kenes would then describe in which area of technology a firm masters which ability and to which level of expertise. As an example, a technology could be ‘capability 2: computer programming’ (kene example 1), ‘capability 56: relational data processing’ (kene example 2), or ‘capability 665: organic chemistry’. Abilities are interpreted as the specific process, methodology or technique: ‘ability 3 (in the area of computer programming: front
end development’, ‘ability 67 in the area of relational data processing: data histogram generation’, or ‘ability 6.7678876 (in the area of organic chemistry): polymerisation’. Abilities are defined as floating numbers. The expertise level captures the level of experience with the capability and ability the firm possessing this kene has. In kene example 1, the firm would have the experience level 5 (out of 10) in the area of computer programming, more specific, front end development. A firm possessing kene example 3 would have a very low level of experience in the area of organic chemistry, more specifically polymerisation.

![Kene dimensions](image)

From this kene set, a firm selects a certain number of kenes randomly, calling the sub-set an innovation hypothesis (IH). In this example, the firm would combine kene example 1 and kene example 2. Using an modulus algorithm (representing uncertainty) which combines all capabilities and abilities in the IH, a product number is generated. This product number represents the product determines whether the respective product can be either used as an input in other firms’ IHs or is sold to the end user (see subsequent paragraph about market mechanisms).

Kene dimensions are changed either based on market feedback (see paragraph 3.5.3) or based on successful application. If a kene is successfully applied in a product, its expertise level increases with the number of applications (learning by doing). As a result, the quality of the product raises. If a kene is not used in the IH of the firm for more than a certain number of periods, it is forgotten and deleted from the set of kenes of the firm. If a product is not successful, the firm engages in incremental research. For this, a ‘tax’ has to be paid and the ability is changed in a random direction (single loop learning). The recalculated product is put on the market again for selling. Firms which do not succeed for a longer time in product selling despite incremental research, opt for radical research. This changes one or more capabilities in the kene set and again, the product is recalculated. If research leads to a successful product the firm stops doing research. The
learning processes modelled in SKIN are based on the theory of organisational learning as introduced by Argyris and Schön (1996).

Also on the knowledge level networks emerge: fully connected sub-networks can be constructed based on all capabilities in the IH of a successful product. If a capability is used for the production of two different products in two different firms, both sub-networks become connected via the respective capability. Based on this, Chapters 5.4 analyses the knowledge dynamics in the SKIN model.

3.5.3 Markets

Products are exchanged via a market process in which feedback in the form of number of sales causes firms to react either with a change in price or knowledge base through research. The market price is based on the price of the inputs (cost-pricing), and a margin is added. Below a certain number of sales, the price is lowered, above the threshold it is kept stable or increased. Products are not sold below production price.

As described above, based on the IH of a firm, a product number is calculated. A predefined product space is used to determine the type of product for a product number (e.g. 1-100). High product numbers (e.g. >90) indicate that the product is an end-user product, meaning that the product is sold at a predefined maximum price. If the product number is higher than the threshold for determining raw materials and lower than the threshold for end-user products (e.g. 10 < product number < 90), the product can only be used as inputs in other firms' IHs. A firm which needs this product as an input for its IH would buy the respective product on the market. In case two products with the same product number and price are available at the market, expertise levels are used to calculate the quality of the product. The quality of the product would then be used by input-seeking firms (and end-users) as a further selection criteria.

In order to determine the inputs needed for the production process, the IH is sliced up, again calculating the product number of each of the sub-sets. If the resulting input product number is below a certain threshold (e.g. < 10), the input is a raw material and therefore always available on the market. Through this process, value chains emerge in the simulation based on which the dissemination of knowledge through products can be inspected.
4 Data

The data used for the empirical study is generated from the Delphion database that covers all patents filed at the United States Trademark and Patent office (USPTO). The USPTO holds a more detailed database than its European counterpart, the European Patent Office. All patents are extracted that have been assigned to at least one person or organisation located in the Republic of Ireland (ROI) beginning in the year 1978 to 2011\textsuperscript{15}. Since we focus our investigation on knowledge of economic importance for Ireland - knowledge that could be used for innovation and production patents assigned to companies in the Republic of Ireland, and not the ones invented in Ireland, are considered.

Nanotechnology patents are identified by the boolean keyword search for the term “nano*” (compare Hu et al. 2011). We choose Boolean keyword search instead of IPC classification Y01N (nanotechnology) to find patents related to nanotechnology, as in the rapidly expanding field of emergent technologies keyword search provides a more precise identification of nanotechnology patents (Bhattacharya and Shilpa 2011). A separate IPC class for nanotechnology has been established only shortly before data collection (Dolfsma and Leydesdorff 2011). It is not applied by the USPTO up until now. IPC classifications are nevertheless assigned to the data obtained by Boolean search, as it will help us to identify distinct clusters of knowledge and the sectors affected by nanotechnology (e.g. measurement, materials, pharmaceuticals, semiconductors). IPC classes have been matched to industry sectors for approximately 30% of all classes, including the most important ones by node degree.

The search returned 2953 patents assigned to at least one Irish person or organisation. The dataset was then split into two sub-sets. The first sub-set includes all patents related to nanotechnology (225 patents that contain the term “nano*” in their title or abstract; subsequently referred to as nanotechnology patents - NP). The second sub-set contains patents unrelated to nanotechnology (2728 patents without a direct relationship to the term “nano*”; further referred as “other patents” – OP). Prior to further analysis and graph creation all items without IPC code information were deleted from the dataset (252 items).

\textsuperscript{15} Although the number of patents granted in one year may be affected e.g. by the availability of human resources at the respective patent office, aggregation among multiple years smoothens these differences and provides and insight into the overall structure of the network.
5 Research

Chapter 5 consist of 4 publications and one section of unpublished work in progress.

5.1 Publication 1: Nanotechnology in Ireland – an analysis of the patent co-classification network

Research questions:

Q1: Is nanotechnology connecting previously unconnected areas?
Q2: How can these structures be measured and visualized (for later model validation)?

An empirical study is presented based on the patent co-classification network of all patents with at least one assignee located in Ireland. In this sense it is restricted to the national system on innovation in Ireland. The technological focus however is on nanotechnology. Revealing the structure of the Irish co-classification network, the analysis reveals that nanotechnology is tending to connect previously weakly or unconnected technology areas.

The implications for policy making are twofold. A sound technology policy aiming at fostering nanotechnology research and innovation should on the one hand not focus in too great detail on the technology sector in which nanotechnology is applied (e.g. application of nanotechnology in the area of semiconductors), as this might disregard the effect a transfer of this nanotechnology knowledge and its application in other sectors has. On the other hand, a technology policy which is too general might neglect the characteristics of each sector in which nanotechnology is applied. This trade-off underlines the additional degree of complexity which confronts policy makers in the case of nanotechnology and general purpose technologies at large.
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Abstract
In this article we investigate how the knowledge networks for an emergent technology are structured, taking nanotechnology in the Republic of Ireland as an example. We construct knowledge networks by mapping all patents assigned to the Republic of Ireland in the period from 1978 to 2011, using IPC patent classes as proxies for codified knowledge. We then analyse the geodesic path length in these networks to determine if nanotechnology exhibits multidisciplinary or interdisciplinary characteristics. Our results indicate that nanotechnology is an interdisciplinary phenomenon: it takes root in one discipline and then spreads among different fields over time. Our findings imply that policy makers could foster the development of nanotechnology by intervening in areas of proximal development of already existing competencies.

Key Words: nanotechnology, networks of knowledge, patent network analysis, co-classification.

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5.1.1 Introduction
Nanotechnology – named as ‘the key-technology of the 21st century’ (Bhattacharya and Shilpa 2011) - is often defined as technology to manipulate and control matter at the scale 1-100 nanometres. Nanotechnology represents an interesting case for the scholars of emergent technologies, as it is applied across a variety of sectors: from the information and communication technology (ICT) to biotechnology, and from the pharmaceutical industry to material science and manufacturing. Although nanotechnology as a scientific field substantially impacts socio-economic development of the European economy, it is particularly important for the Republic of Ireland, as the country holds a revealed technological advantage in nanotechnology compared to other countries of Western Europe (OECD 2009). At the same time the Republic of Ireland also hosts strong
Considering the importance of the nanotechnology sector in Ireland, an important question arises how its development could be sustained and fostered. What are the principles that drive the growth and evolution of nanotechnology? Although research recently generated a lot of helpful insights into the scope, structure and dynamics of the nanotechnology field (Yu et al. 2010), the debate is still out with regards to characteristic patterns of knowledge generation and diffusion in the nanotechnology sector. As patterns of knowledge diffusion are often considered major prerequisites for innovation, it is essential to understand how knowledge is generated, structured and propagated throughout the network. These processes are of particular importance for policy makers, as awareness of the knowledge diffusion patterns helps to design efficient policy measures and interventions for fostering knowledge transmission.

As nanotechnology is represented across different industries and scientific fields, it is essential to understand if nanotechnology develops in an interdisciplinary or multidisciplinary (Miyazaki and Islam 2007, Schummer 2004) manner. Does nanotechnology exhibit an interdisciplinary nature, originating in one discipline and then spilling over to the related fields? Or does it follow a different pattern, taking root in multiple disciplines and then converging across fields over time? Knowing how nanotechnology propagates among different fields would help practitioners to target policy interventions more efficiently, which in turn would enable synergies in knowledge commercialisation and innovation diffusion.

In this contribution we use nanotechnology and non-nanotechnology patents to represent the relevant knowledge base (KB) in the Republic of Ireland. Thus we map the co-classification network of all patents – those related as well as unrelated to nanotechnology – having at least one assignee in the Republic of Ireland. We chose Ireland as the country that pioneered multiple nanotechnology applications and hosts many industry sectors that apply nanotechnology. Therefore, nanotechnology in Ireland graphically illustrates how the knowledge is structured in this emergent field. We contribute to the debate about the interdisciplinarity and multidisciplinarity of nanotechnology by providing a visual and descriptive network analysis of the empirical case of Ireland in order to be able to investigate how and where nanotechnology connects to other knowledge available to the economy.

5.1.2 Theoretical Background

The knowledge base of a firm, region or nation constitutes a critical factor (Saviotti et al. 2005) for thriving in the modern knowledge based economy (OECD 1996). Although in
early theories knowledge is represented as a simple and homogenous input factor for the production function (see e.g. Griliches 1979), recent evolutionary approaches (Krafft et al. 2011, Saviotti 2007, 2009) treat knowledge as a system and differentiate between two important properties of knowledge: (1) its interpretative or retrieval structure and (2) its co-relational structure. In this evolutionary framework (Saviotti 2009), knowledge could be represented as a network: a structure of units (concepts, publications or patent classes) and links between these units (e.g. the joint utilization of concepts or co-citations among patents or papers). The systemic approach allows us to represent how knowledge accumulates through re-configuration of available knowledge units and emergence of new ones (Krafft et al. 2011). This approach could be applied to characterise the knowledge base of various systems: companies, industry sectors or nations. Proxies for the knowledge base of these systems can be found for instance in publications and citation patterns among them (Onel et al. 2011), as well as patents and their co-citations (Breschi et al. 2003). In our approach, we are focussing not on publications, but on patents and their co-classifications as previously conducted by other researchers using patent co-classification to analyse the knowledge base of sectors (Krafft et al. 2011), companies (Breschi et al. 2003) and nations (Dolfsma and Leydesdorff 2011).

To understand how policy makers could foster the development of the knowledge base for an emergent technology, we focus our investigation on the national innovation system (Nelson 1993), taking Ireland as an example. The knowledge base of a national innovation system can be seen as the combination of the individuals’ knowledge, represented in patents (Saviotti et al. 2005). To understand how the knowledge base is structured, we analyse a network of patent co-classifications (Nesta and Saviotti 2004), taking IPC (International Patent Classification) classes cited in a patent as nodes of the network, and co-occurrence of different classes on the same patent as edges (Krafft et al. 2011).

We can represent the knowledge incorporated in patents related to nanotechnology as a network, visualize it and apply statistical network analysis techniques to reveal how nanotechnology is related to other areas of knowledge. The following changes in the structure of the knowledge network characterize an emergent knowledge base (Krafft et al. 2011): i) new nodes appear, ii) old nodes (old knowledge) dissolve, iii) new connections form between nodes or clusters (e.g. links between new and old knowledge appear within the network) and iv) nodes’ position in the system changes. In these analyses, innovation is captured when new connections are formed between the knowledge units, or when new nodes – patent classes – appear.
As nanotechnology has a broad range of applications across multiple fields, we are interested in how nanotechnology and other technologies are connected. A co-classification analysis reveals how nanotechnology is embedded within the broader knowledge (Igami 2008), codified in patents. The nanotechnology literature addresses these interconnections in the interdisciplinarity – multidisciplinarity debate.

It is essential to understand how new knowledge is embedded into existing scientific disciplines, as it will enable us to identify possible areas for policy intervention. Interdisciplinarity implies that nanotechnology connects previously separated fields and leads to convergence between them. Multidisciplinarity characterizes a mix of loosely connected, weakly or not at all integrated scientific disciplines. In this sense a new technology serves as an “amalgam of relatively traditional pockets” (Porter and Youtie 2009, p. 1023).

Debate is still out on whether nanotechnology exhibits an interdisciplinary or a multidisciplinary nature. Some researchers emphasise the multidisciplinary characteristics of nanotechnology. Schummer (2004) investigates co-authorship networks in nanotechnology publications and concludes that nanotechnology is a multidisciplinary phenomenon: nanotechnology connects more or less unrelated disciplines such as nano-physics, nano-chemistry, nano-electrical engineering or nano-biotechnology. According to Schummer (2004), nanotechnology does not show a higher degree of interdisciplinarity than other disciplines. Porter and Youtie (2009) corroborate the idea of multidisciplinarity by demonstrating that nano-related disciplines do not converge over time: the network links between nanotechnology and other disciplines remain relatively constant from 1991 to 2005. In their analysis nanotechnology clusters around material sciences, showing a high degree of disciplinary diversity or multidisciplinarity.

Similarly, Meyer (2007) points to the high degree of specialization among companies active in the field of nanotechnology: most companies focus on one specific nano-scale technology. This indicates that nanotechnology could be considered as a general-purpose technology, applied among – but not leading to convergence of - various industrial sectors.

Rafols and Meyer (2007) demonstrate that the degree of interdisciplinarity varies depending on the indicator chosen: interdisciplinarity is high in the subfield of bio-nanotechnology if references or instruments from other scientific disciplines are used as an indicator; interdisciplinarity is low if the background of researchers and their affiliation are considered. From these studies, Huang et al. (2010) conclude that the question of interdisciplinarity very much depends on the definition of ‘interdisciplinarity’.
Although the debate is still out if nanotechnology fosters convergence among various scientific fields and existing technologies, Meyer (2007) observed that the sub-discipline ‘instrumentation’ connects nanotechnology clusters. The ICT sector - an established, mature technology field - developed many instruments for nanotechnology from the early stages of nanotechnology. There is discussion however, about the origins of nanotechnology: is nanotechnology a radically new technology which was first developed as a rather independent technology and was applied later in other sectors, or did nanotechnology incrementally develop from the advances e.g. in the microelectronics sector (Meyer 2007)?

In this Chapter we address this question by examining the network structure between nanotechnology and related fields. We rely on the nanotechnology patent co-classification network to provide insights on how nanotechnology is embedded within other disciplines. We suggest that if nanotechnology is multidisciplinary, there would be sparse links between most knowledge areas and this should be reflected in the co-classification network. Some nanotech knowledge fields - such as instrumentation - would connect those formerly separated disciplines.

As Igami (2008) states, nanotechnology patent applications are distributed differently among the EU countries. Due to path dependence, knowledge in nanotechnology accumulates and clusters around established scientific fields. As Ireland has strong biotechnology and ICT sectors, we could expect high activity in these areas. Nanotechnology activity would be low in areas that are peripheral to the Irish knowledge base. As nanotechnology develops, new nodes attach to established clusters, building upon already existing knowledge and competencies. This effect – first deepening and then the subsequent widening of specialization (Menz and Ott 2011) – determines the dynamics of pathways between previously disconnected fields and gives a first indication of the type of logic that drives nanotechnology evolution.

We argue that nanotechnology would exhibit interdisciplinary network structures in patent co-classification networks as shorter geodesic paths between different network clusters would be established.

Hypothesis: The average path length of the network should be significantly lower in a network with nanotechnology than in a network without nanotechnology.

5.1.3 Methods and data

We chose Ireland as an example for a National Innovation System for several reasons. First, nanotechnology in Ireland represents a critical case: Ireland is a champion in the field of nanotechnology in Western Europe. According to the OECD (2009), it is the country with the highest revealed technological advantage in this area. Therefore from
Ireland we can learn how knowledge could be successfully integrated and can understand better the processes behind the emergence and dissemination of nanotechnology within the nation’s entire economy.

Second, nanotechnology had a profound effect on two fundamental pillars of the Irish economy: ICT and biotechnology sectors. Although nanotechnology originated in the field of the microprocessor manufacturing - which is a cornerstone of Ireland’s ICT industry (Choi and Mody 2009) - both ICT and biotech sectors host a variety of practical nano-applications.

Third, Ireland prioritized nanotechnology and some specific fields within it (Materials, Biotech and ICT) and is keen to understand which policy measures could be applied to amplify technological development in this area (Forfás 2010). Therefore, Ireland is a particularly interesting case for technology policy assessment.

As patents are considered to be an appropriate proxy for scientific and technological knowledge (Bhattacharya and Shilpa 2011), we generate our dataset from the Delphion database that covers all patents filed at the United States Trademark and Patent office (USPTO), which holds a more detailed database than its European counterpart, the European Patent Office. We extract all patents that have been assigned to at least one person or organisation located in the Republic of Ireland (ROI) beginning in the year 1978 to 201116. We focus our investigation on knowledge of economic importance for Ireland - knowledge that could be used for innovation and production. Therefore, patents assigned to organisations or persons in the Republic of Ireland, and not the ones invented in Ireland, are considered.

Nanotechnology patents are identified by the boolean keyword search for the term "nano*" (cf. Hu et al. 2011). We choose Boolean keyword search instead of IPC classification Y01N (nanotechnology) to find patents related to nanotechnology, as in the rapidly expanding field of emergent technologies keyword search provides a more precise identification of nanotechnology patents (Bhattacharya and Shilpa 2011). A separate IPC class for nanotechnology has been established only recently (Dolfsma and Leydesdorff 2011). It is not applied by the USPTO up until now. IPC classifications are nevertheless assigned to the data obtained by Boolean search, as it will help us to identify distinct clusters of knowledge and the sectors affected by nanotechnology (e.g. measurement, materials, pharmaceuticals, semiconductors). IPC classes have been matched to industry sectors for approximately 30% of all classes, including the most important ones by node degree.

16 Although the number of patents granted in one year may be affected e.g. by the availability of human resources at the respective patent office, aggregation among multiple years smoothen these differences and provides an insight into the overall structure of the network.
The search returned 2953 patents assigned to at least one Irish person or organisation. The dataset was then split into two sub-sets. The first sub-set includes all patents related to nanotechnology (225 patents that contain the term "nano*" in their title or abstract; subsequently referred to as nano patents - NP). The second sub-set contains patents unrelated to nanotechnology (2728 patents without a direct relationship to the term "nano*"; further referred as "other patents" – OP). Prior to further analysis and graph creation all items without IPC code information were deleted from the dataset (252 items).

Co-classification analysis has been widely used: to identify how knowledge relatedness explains firms’ technological diversification (Breschi et al. 2003); to analyse the structure of the biotechnology knowledge (Krafft et al. 2011); and to investigate how Dutch and Indian innovation systems affect the nanotechnology knowledge base (Dolfsma and Leydesdorff 2011). This method enables policy makers to grasp how the knowledge structure and the innovation system are interconnected, and how manufacturing structure - which depends on available knowledge - may evolve in the short run. Dolfsma and Leydesdorff argue that knowledge from one class would be transferred and applied more easily to another class if co-classification is found. Knowledge codified in patents and thus patent data can be used as an indicator for potential and actual knowledge flows within the respective system, e.g. within a company or networks within a national innovation system (Dolfsma and Leydesdorff 2011). Using classes as nodes in a network is based on the assumption that these nodes represent discrete concepts, which otherwise would lead to a multi-level network. Since IPC classes are a hierarchical system with discrete cuts between the classes (Leydesdorff, Kushnir and Rafols 2014), these classes can be considered to be suitable for a unimodal network analysis.

The hypothesis is tested with three co-classification analyses, one for each dataset: sub-set of nanotechnology patents (NP), sub-set of all other patents (OP, Irish patents that do not mention nanotechnology), and the combined dataset. Table 1 reveals the network statistics for all three datasets. The combined dataset allows us to visualize how nanotechnology network connects to other fields and to investigate the effects of the links which come only into existence by the combination of the two datasets, i.e. the links which describe the connections between NP and OP. We use the Gephi software package (Bastian et al. 2009) to visualize and analyse patent networks.

5.1.4 Results
The share of nanotechnology patents in the Irish nanotechnology KB is steadily increasing from about 2 percent in the year 1998 to about 8.4 percent in 2010 (see Table 1 and Figure 13). Within the same time span the share of new nanotechnology patents
on all new patents ranges from 4.6 percent in 1998 to around 20 percent in 2009, with
the absolute number of new nanotechnology patents remaining relatively stable from
2009 at approximately 30. Although Schmoch and Thielmann (2012) argue that
nanotechnology evolution has reached a phase of stagnation, our data indicate that
nanotechnology steadily increases in importance for the Irish economy and knowledge
base over the last decade.

The patent co-classifications map for all nanotechnology related patents reveals the
strong prevalence of organic fine chemistry and pharmaceuticals (coloured in red). A
high level of detail is used to classify patents: sections, classes and subclasses. In
figures 15 and 16, the node size represents betweenness centrality (larger nodes have
higher betweenness centrality). Nodes yellow indicate electrical engineering (mainly ICT,
including semiconductors), nodes blue biotechnology and nodes green basic materials
chemistry. The graph contains 334 components, having a low graph density of 0.022.
The giant component consists of 3149 nodes and 34935 edges. This means that 67.82%
of all nodes and 91.84% of all edges are included into the giant component.

In figures 16 and 17 all edges related to a nanotechnology patent are coloured in red, all
others in blue. Visual inspection reveals that all edges in the network related to
nanotechnology are connected to the giant component. This indicates the
interdisciplinary nature of nanotechnology development, as newly added patent classes
are directly related to classes that are already included in other patents. Figure 18 shows
all nanotechnology related patent classes as a co-classification network. The network
shows little coherence, however not contradicting the notion of a rather path-dependent
development. It can be explained by nanotechnology patents being attached to a number
of differing technology areas in the knowledge base which are not necessarily connected
either directly or via a nanotechnology patent class.

Both, the OP as well as the combined network show similar average clustering
coefficients (0.786 and 0.782 respectively). With 0.859 the average clustering coefficient
of the NP network is higher. Average path length is highest for the OP network (5.945),
5.505 for the combined network and 2.71 for the NP network. With only the average path
length being lower in the combined network, the results provide support to our
hypothesis, which suggested that the average path length in the combined networks
should be lower than in the OP network. In that sense nanotechnology can be seen as
technology, that connects formerly unconnected areas of the network more directly due
to its interdisciplinary nature.

However, further investigation into the evolution of betweenness centralities (see below)
is needed to further strengthen the statement of interdisciplinarity and a possibly
significant impact of nanotechnology on the average path length.
Betweenness centralities are calculated for the detailed dataset of the combined and the nanotechnology network according to the following definition by Brandes (2001):

Let $\sigma_{st} = \sigma_{ts}$ describe the number of shortest paths from $s \in V$ to $t \in V$, where $\sigma_{st} = 1$, $V$ describes the set of all vertices (nodes) in the network. And let $\sigma_{st}(v)$ describe the number of shortest paths (edges) from $s$ to $t$ that some $v \in V$ lies on.

The betweenness centrality $C_B$ of node (or vertex) is then calculated as follows:

$$C_B(v) = \sum_{s \neq c \neq t \in V} \delta_{st}(v)$$

This equals the sum of the pair-dependencies of all pairs on that node (or vertex). The pair dependencies are given by

$$\delta_{st}(v) = \frac{\sigma_{st}(v)}{\sigma_{st}}$$

of a pair $s, t \in V$ on an intermediary $v \in V$. i.e. the ratio of shortest paths between $s$ and $t$ that $v$ lies on, is given by:

$$\sigma_{st}(v) = \begin{cases} 0 & \text{if } d_G(s, t) < d_G(s, v) + d_G(v, t) \\ \sigma_{sv} \cdot \sigma_{vt} & \text{otherwise} \end{cases}$$

The almost unchanged average clustering coefficient might be interpreted as nanotechnology introducing additional, equally clustered IPC class-cliques.

Figures 21 and 22 show the co-classification map of all patents having an assignee located in the ROI. The OP network has 4270 nodes (classes), the nanotechnology network has 712 classes. When combined, only 4643 classes are mentioned. Thus, there are 373 nanotechnology specific classes, which are added because of their appearance on a nanotechnology patent.

The betweenness centrality measures how often a node “is located on the shortest path (geodesic) between other nodes in the network” (Leydesdorff, 2007, p. 1304). It therefore also takes into account all indirect links of the respective node and is normalized by the number of all geodesic distances in the graph. In Figure 17 the highest 500 values of the combined and the NN network are plotted, whereas for the nanotechnology network, all values are included (191 values). In general, betweenness centrality can be taken as an indicator for interdisciplinarity (Leydesdorff 2007). Future research could address how the betweenness centrality distributions evolve.
5.1.5 Discussion and Conclusion

With its widespread applicability and thus economic potential, nanotechnology is on the one hand of great interest for policy makers. For this reason it is important to understand which factors influence the evolution of this emerging technology and which policy instruments could be applied to foster knowledge integration for the economic benefit. This applicability on the other hand also raises the question how this new technology relates to already existing knowledge areas. Scholars quested to understand the developmental trajectories of nanotechnology by focusing on how nanotechnology is embedded within the adjacent disciplines and looked for the multidisciplinary or interdisciplinary indicators of its development. We focussed on the question whether Nanotechnology is more multidisciplinary, thus affecting other technologies in an uncorrelated way, i.e. does nanotechnology affect several other technology areas but it does not establish potentially new connections between the affected areas. Or if nanotechnology is more interdisciplinary, bringing existing areas of knowledge together.

For our case study we chose Ireland and the patents in the Irish patent portfolio, as it already has a competitive edge in the field of nanotechnology and its applications. Evidence suggests that nanotech develops incrementally, in the interdisciplinary manner. With the network representation of the knowledge available to Irish companies in the form of the patents, we looked at whether the nanotechnology network in Ireland also spans several unrelated technology areas. Our analysis indicates that nanotechnology loosely connects various fields of knowledge, providing some support for nanotechnology being of interdisciplinary nature.

Further questions remain however. Evolutionary analyses of the networks may reveal whether a multidisciplinary character within the networks is a permanent or temporary phenomenon. In other words, does it change from earlier stages of the network evolution to later ones? Interdisciplinarity in this sense might be only a recent phenomenon that could gain in importance over time. This would imply even more newly established connections would bridge nanotechnology with various application areas. If so, fostering the establishment of these interdisciplinary bridges may hold great potential for innovation: novel patent class combinations could be promising areas for policy interventions. A citation analysis would provide more detailed insights: patents often cite from other technology areas without being classified in these. Citation mapping might unveil direct links between various technologies (Igami 2008).

Our results implicate several consequences for policy making: If nanotechnology is multidisciplinary and thus its application areas constitute a loosely connected selection of different sectors, a targeted policy approach for each nanotechnology application sector (e.g. nano-biotechnology or nano-chemistry) would be possible. A piece or set of
pieces of nanotechnology would only be in the realm of biotechnology, while another piece of nanotechnology would only be applicable within chemistry. In this way, policies targeting the one or the other field may be possible without bearing unexpected effects in the respective other field of application. It would also be easier to prioritise certain sectors. Considering unforeseeable developments, i.e. when during the evolution of a specific piece of nanotechnology, unforeseeable applicability in other sectors emerges, a close monitoring of the developments of the technology will be necessary to enable timely policy adjustments. Identifying what nanotechnologies have the highest impact and do fit best into the already existing industrial knowledge network would be prerequisite for developing and implementing a targeted policy. This is to help policy makers to allocate resources accordingly and to focus on the commercialisation of certain nanotechnologies, as is proposed in the Irish Nanotechnology Commercialisation Framework (Forfás 2010).

Based on the results of this study, currently, a targeted policy approach seems possible since the different application fields only seem loosely connected. This may change over time of course. Provided nanotechnology evolves into an interdisciplinary field in which a piece of nanotechnology may be applied in different technology sectors, this will result in a much stronger interconnectedness between the sectors. Thus, specific policies targeting a certain application sector may result in unexpected effects. Policies would need to account for this in consequence to target more general aims.
5.1.6 References


## Appendix

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Table 1: Descriptive statistics Irish patents
Fig. 16: Annual and cumulative share of nanotechnology patents, in %

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<th>Nano patent network</th>
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<td>Nodes</td>
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Table 2: Descriptive network statistics
Fig. 17: Betweenness centrality distributions

Fig. 18: Co-classification map of nanotechnology patents in Ireland
Fig. 19: All patents co-classification map

Node colours
Yellow: electrical engineering
Blue: Biotech
Green: Basic materials chemistry
Red: organic chemistry and pharmaceuticals
Fig. 20: Detail of figure 16
5.2 Publication 2: Responsible, Inclusive Innovation and the Nano-divide

Research question:

Q3: Can the descriptive SI framework be used to integrate normative questions which arise from the emergence of nanotechnology?

With the emergence of nanotechnology, debates about the access to and the attractiveness for nanotechnology products arise – known as the nano-divide. This can be regarded as a recent example of a policy discourse entailing normative goals, such as justice regarding the benefits of nanotechnology. At the same time with RRI, there is another current debate mainly held in Europe about the integration of ethical goals into R&I policy in order to increase competitiveness and thus growth and welfare. An integration of the aims of both debates may result in a set of goals which is more easily to reach.

The following publication tackles the question whether the framework outlined in chapter two - the descriptive Systems of Innovation approach including its analytical set of tools such as SNA and ABM can be utilized to analyse, model and evaluate innovation systems with respect to the implementation and achievement of both, goals of growth based on innovation, and the solution of societal issues at the same time.

If so, the aims of such policies could be reflected and hence analysed by innovation system analysts. The paper shows how these concepts can be linked in order to build a bridge between a normative concept, the descriptive theory of the SI approach including its set of tools (such as SNA and ABM). As such, with the SI approach policy interventions with normative aims may be validated as well – making the framework even more attractive for policy modellers and policy makers especially with regard to nanotechnology as a GPT and the debates arising with its emergence.
Abstract
Policy makers from around the world are trying to emulate successful innovation systems in order to support economic growth. At the same time, innovation governance systems are being put in place to ensure a better integration of stakeholder views into the research and development process. In Europe, one of the most prominent and newly emerging governance frameworks is called Responsible Research and Innovation (RRI). This article aims to substantiate the following points: (1) The concept of RRI and the concept of justice can be used to derive similar ethical positions on the nano-divide. (2) Given the ambitious policy aims of RRI (e.g. economic competitiveness enhancer), the concept may be better suited to push for ethical outcomes on access to nanotechnology and its products rather than debates based on justice issues alone. It may thus serve as a mediator concept between those who push solely for competitiveness considerations and those who push solely for justice considerations in nanotechnology debates. (3) The descriptive, non-normative Systems of Innovation approaches (see below) should be linked into RRI debates to provide more evidence on whether the approach advocated to achieve responsible and ethical governance of research and innovation (R&I) can indeed deliver on competitiveness (in nanotechnology and other fields).

Keywords:
Inclusive innovation; Innovation governance systems; Nano-divide; Responsible research and innovation; Systems of innovation approaches

5.2.1 Introduction
Academics, innovators and policy makers have for decades been interested in the dynamics that have made Silicon Valley a success (see also Table 3). Innovation and innovation systems are becoming increasingly interesting to policy makers for achieving their economic and social goals. In Europe, “79% of companies that introduced at least one innovation since 2011 experienced an increase of their turnover by more than 25% by 2014” (European Commission n.d.).

17 For instance, a reduction in unemployment through economic growth.
As a result, policy makers from around the world are trying to emulate successful innovation systems in order to support economic growth. For instance, academics, innovators and policy makers have for decades been interested in the dynamics that have made Silicon Valley a success (see also Table 3). At the same time and following negative societal responses to genetic modification around the world, innovation governance systems are being put in place to ensure a better integration of stakeholder views into the research and development process. In Europe, one of the most prominent and newly emerging governance frameworks is called Responsible Research and Innovation (RRI) (European Commission 2016).

The article is in four parts. The first part provides background, definitions and clarifications about the terms innovation, innovation systems and responsible research and innovation. The second part will consider the question of the nano-divide with reference to RRI. The third part will introduce the concept of inclusive innovation to bridge the gap between innovation systems and RRI. Finally, the fourth part will try to substantiate the following three points in a conclusion.

1. The concept of Responsible Research and Innovation and the concept of justice can be used to derive similar ethical positions on the nano-divide.\(^\text{18}\)

2. Given the ambitious policy aims of RRI (e.g. economic competitiveness enhancer), the concept may be better suited to push for ethical outcomes on access to nanotechnology and its products than debates based on justice issues alone. It may thus serve as a mediator concept between those who push solely for competitiveness considerations and those who push solely for justice considerations in nanotechnology debates.

3. The descriptive, non-normative Systems of Innovation approaches (see below) should be linked into RRI debates to provide more evidence on whether the approach advocated to achieve responsible and ethical governance of R&I can indeed deliver on competitiveness (in nanotechnology and other fields).

5.2.2 Innovation, Innovation Systems and Responsible Research and Innovation

Innovation has been defined as follows:

Innovation is an activity or process which may lead to previously unknown designs pertaining either to the physical world (e.g. designs of buildings and infrastructure), the conceptual world (e.g. conceptual frameworks, mathematics,

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\(^{18}\) Considerations of justice are not often discussed in the context of RRI. An example exception is (UN 2002).
logic, theory, software), the institutional world (social and legal institutions, procedures and organization) or combinations of these, which - when implemented - expand the set of relevant feasible options for action, either physical or cognitive (van den Hoven et al. 2013).

Innovation is widely regarded as the key ingredient to national economic success. For instance, China, the country which was most successful world-wide in terms of economic growth in 2013 (7.7%) (CIA n.d.), recently launched structural adjustment policies to move from manufacturing growth towards a knowledge and innovation economy. In 2012, the 18th National Congress of the Communist Party of China proposed a reform of the science and technology system to improve the potential for innovations across all sectors (David Coles et al. 2014).

As innovation has become central to economic success, policy makers and researchers are increasingly interested in understanding what factors enhance innovation. A range of descriptors have emerged for fields that examine the innovation process from knowledge creation to commercialisation (e.g. Innovation Studies, Science Studies, Science and Innovation Studies, Science and Technology Studies). One of the fields’ most prominent outputs is the Systems of Innovation approach. The three main Systems of Innovation approaches are, the National Systems of Innovation approach (NSI), the Regional Systems of Innovation approach (RSI) and the Sectoral / Technological Innovation Systems approach (S-TSI), see Table 3.

<table>
<thead>
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<th>National Systems of Innovation (NSI)</th>
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<td>Adopting a holistic view of innovation rather than focussing on isolated aspects of the process, the NSI concept emphasises the interaction of actors involved in innovation and analyses how these interactions are shaped by social, institutional and political factors (Fagerberg and Verspagen 2009). NSI was remarkably successful in a short period of time and is now being used in academia and policy contexts (Teixeira 2013). It is often used as an analytical framework (Sun and Liu 2010) for studying the differences between countries concerning their production and innovation systems (Álvarez and Marín 2010).</td>
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<th>Regional Systems of Innovation (RSI)</th>
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<td>The NSI approach assumes homogeneity within countries, but this is not necessarily the case. On many indicators (e.g. economic performance, poverty, R&amp;D investment) countries can differ significantly within their own boundaries. As a result, researchers and scholars of innovation systems have developed a regionally-based approach of innovation system thinking, with</td>
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‘regions’ usually referring to a geographical area within a country. In some instances, cross-border regions are also possible, the Saar Lorraine region being an example, which spreads across France and Germany and which shows considerable collaboration in local economic affairs. The research focus in the Regional Systems of Innovation (RSI) concept therefore rests on the relationship between technology, innovation and industrial location (D’Allura et al. 2012). This spatial concentration remains important for innovative activities, despite the argument that modern information and communication technologies would render spatial distances between communication partners unimportant (Asheim and Gertler 2005). Silicon Valley is normally used as the prime example of a region with great innovative potential.

### Sectoral / Technological Systems of Innovation (S-TSI)

Unlike the innovation system approaches described above, which both rely on a spatial dimension to define their boundaries, the sectoral/technological innovation system approaches adopt either a certain technology (spanning multiple sectors), or the sector in which it is used (including various technologies) as their system boundary. The notion that particular sectors have different technological trajectories was first spelt out by Dick Pavitt (Pavitt 1984). The concept of sectoral innovation systems was further developed by Malerba (Malerba 2002), whereas the development of the technological approach can be traced back to Carlsson and Stankiewicz (Carlsson and Stankiewicz 1991). Both concepts are less developed than the NSI and the RSI approaches, and have a smaller overall impact. In both approaches, links between firms and other organisations are portrayed as occurring as a result of the technological interdependence of their knowledge (Chang and Chen 2004).

#### Table 3: Systems of innovation approaches

Apart from the distinctions given in the above table, all three Systems of Innovation (SI) approaches share certain characteristics. They all place great emphasis on the learning process (Johnson et al. 2003) in which all actors involved (e.g. firms, consumers, universities, public organisations) experience 'learning-by-doing', or learn from each other by exchanging knowledge. Systems of innovation are always defined as complex systems (Metcalfe and Ramlogan 2008), stressing their non-linear, systemic, interactive and evolutionary character [18, 19]. Furthermore, the performance of all SI approaches is analysed in a similar way, namely through the ex-post, historical analyses of economic or innovative activity and knowledge diffusion (Godin 2006a). Such analyses are holistic.
and interdisciplinary, bringing together scholars and analysts from various disciplines to account for the many and complex interactions in the system (Johnson et al. 2003). The attractiveness of SI approaches for policy makers is the fact that they can draw attention to strengths and weaknesses in the innovation system (Soete et al. 2010). However, it is important to emphasize that SI approaches aim to be purely descriptive. These approaches investigate which actors belong to the system, which networks are formed, what the boundaries of the system are, which knowledge is generated, and which internal dynamics can be observed (Coenen and Díaz López 2010). In other words, whilst SI research might describe normative behaviour when found in the innovation process, it tries not by itself to generate any normative conclusions. For instance, policy makers could use research from innovation studies in making funding or tax incentive decisions, based on, for example, the reasoning that successful innovation systems have the potential to reduce unemployment and thereby poverty. For instance, a scheme that provides tax incentives to innovators who are most likely to be successful according to SI research could be defended with reference to job creation and its potential for poverty reduction.

Importantly, innovation is not only seen as a desirable driver of economic growth and prosperity. It can also be highly contentious and even adversarial, particularly in the context of new and emerging technologies, where significant risks for humankind, the environment, local populations, and researchers can occur. It is in this context that the field of Technology Assessment (TA) has been developed (Grunwald 1999) and enhanced (Dusseldorp 2013) as a key mechanism to govern science and innovation. However, by contrast to the beginnings of TA, which were highly expert-driven, newer concepts of innovation governance aim to involve more stakeholders in the innovation process.

In recent years, a new governance framework has become prominent in Europe: Responsible Research and Innovation or Responsible Innovation. The European Commission is highly active in supporting models which govern research and innovation in such a way that societal concerns and interests are taken into account. The ‘Science with and for Society’ (SwafS) programme has produced one of the most influential RRI definitions in Europe:

RRI is an inclusive approach to research and innovation (R&I), to ensure that societal actors work together during the whole research and innovation process. It aims to better align both the process and outcomes of R&I, with the values, needs and expectations of European society. In general terms, RRI implies anticipating and assessing potential implications and societal expectations with
regard to research and innovation (Science with and for Society - European Commission n.d.).

It is noteworthy that the European Commission, which promotes RRI, is also the organisation which drives European competitiveness.

The European Commission places great emphasis on competitiveness, given its importance in creating jobs and growth in Europe. It works to mainstream industry-related competitiveness concerns across all policy areas (European Commission n.d.).

It is also noteworthy that RRI has been linked to increased economic competitiveness in a report published by the European Commission.

The consideration of ethical and societal aspects in the research and innovation process can lead to an increased quality of research, more successful products and therefore an increased competitiveness (van den Hoven et al. 2013).

Interestingly, the European Commission has also issued a range of funding calls to provide more evidence on the link between RRI and increased economic competitiveness. For instance, the call “Responsible Research and Innovation in an industrial context”

aims to contribute towards the innovation and competitiveness objectives of the Innovation Union and to enhanced ‘mainstreaming’ and standardisation of RRI and CSR processes at the EU and Global level.19

Hence, the approach to research and innovation promoted by the European Commission through their understanding of RRI is closely linked to economic competitiveness.

Another RRI definition developed in Europe by Rene von Schomberg defines RRI as a:

[T]ransparent, interactive process by which societal actors and innovators become mutually responsive to each other with a view on the (ethical) acceptability, sustainability and societal desirability of the innovation process and its marketable products (in order to allow a proper embedding of scientific and technological advances in our society) (von Schomberg 2013).

Amongst academics, the most prominent definition of RRI, agreed upon by European and US authors in a joint publication is: “Responsible innovation is a collective commitment of care for the future through responsive stewardship of science and innovation in the present” (Owen et al. 2013). In implementing responsive stewardship, four RRI dimensions are necessary, according to the authors: anticipation, reflection, deliberation and responsiveness.

What all three definitions of R(R)I have in common is that they demand the involvement of a variety of societal actors in the innovation process. They also stress the importance of care, responsiveness, and aligning innovation with societal values and needs.

In this article, we will focus on the most strongly related elements from each definition and link them to nanotechnology. From the SWAFS definition advocated by the European Commission, we will focus on societal needs, which we interpret as global societal needs.

It might be asked why we would jump from the “needs … of European society” to the needs of global society. There are many reasons, and a large literature on cosmopolitanism, but we shall focus on two reasons that can be related to nanotechnology.

Considering only the needs of societies at a national or regional level within innovation governance frameworks disregards the responsibilities Northern states have, historically and currently, for the societal needs of Southern states. Thomas Pogge has successfully illustrated a network of obligations from North to South with concrete examples, which show that these duties do not derive from obligations of benevolence, or charity (Pogge 2007). Intellectual property rights are one instance where innovation governance frameworks systematically favour high income over low and middle income countries (Schroeder 2011). Hence, if innovation governance frameworks that structurally favour one set of agents, including nanotechnology innovators, are in place globally (such as the IPR system), one cannot reasonably limit the extension of another innovation governance framework (RRI) yet again to favour the same set of agents, but this time limit the framework to have only regional significance.

More specifically, and in relation to nanotechnology, it has been argued that “Nanotechnology can be harnessed to address some of the world’s most critical development problems, … [including] challenges faced by the 5 billion people living in the developing world” (Salamanca-Buentello et al. 2005). And, indeed, in a globalized world, one cannot reasonably ignore the potential of the technology for impacting on the lives of the most vulnerable people on earth, by restricting a discussion on its development to the needs of European society. Hence, whilst we use one element from the SWAFS definition of RRI (needs), we believe that its restricted focus on Europe cannot be justified, and we therefore expand the scope of our discussion to be global.

From the von Schomberg definition, we will focus on societal desirability, which we define as follows: “An innovation is societally desirable, if it can benefit all human beings without discrimination”. One could ask why we interpret ‘societal desirability’ to relate to innovations that can benefit all human beings without discrimination. Is that not too demanding? Societal desirability is an inadequately defined term in the literature. Its
strong advocate, Rene von Schomberg, has linked it to the right impacts and outcomes of research (von Schomberg 2013). Trying to answer what such impacts and outcomes are, he links societal desirability to the Grand Challenges of humankind, for instance climate change, public health, pandemics, security (von Schomberg 2013). That is a possible answer, but it is more demanding than ours, and restricts the number of societally desirable innovations even further. Our interpretation of societal desirability does, at least, leave the door open for innovations that have the potential to benefit all of humanity without addressing the Grand Challenges. For instance, Information and Communication (ICT) tools to improve pre-school learning have the potential to benefit all human beings without relating to a Grand Challenge of humanity. Hence, our take on the societal desirability criterion of RRI is less ambitious than the author’s (Rene von Schomberg) and we therefore assume that taking it forward in this article is reasonably justifiable.

This is not to say however that all innovation has to be targeted in such a way that all of humankind must always potentially benefit from it. We believe that von Schomberg’s societal desirability criterion has the potential to widen the sphere of potential beneficiaries of research and innovation, and that such an extension of the concept will distinguish highly responsible from less responsible innovation.

One could also ask, whether societal desirability is not the same as ethical acceptability. Obviously, it is ethically acceptable if all of humankind benefitted from innovations without discrimination. And, after all, ethics is the study of all moral principles and systems as well as the study of right and wrong conduct. Hence, any researcher and innovator responsibilities could fall under this heading. However, to understand what RRI implies, it is important to divide it into more easily understandable pieces. Even though the above broad understanding of ethical acceptability is plausible, we shall use the term here in a more limited manner. For this paper, ethical acceptability will be equated with the demands not fundamentally to transgress societal values, which includes compliance with research ethics (e.g. do not exploit research participants). This means it is understood in a limiting way, linked to “do no harm”. By contrast, societal desirability is understood as “do good”. For instance, Article 15 (1) of the UNESCO Declaration of Bioethics and Human Rights requires that:

Benefits resulting from any scientific research and its applications should be shared with society as a whole and within the international community, in particular with developing countries (UNESCO 2005).

This would then relate to societal desirability whilst most other articles in the Declaration relate to ethical acceptability (e.g. Article 4 on harm, Article 6 on consent).

Thirdly, we will focus on responsiveness, which Owen et al interpret as:
Using a "collective process of reflexivity to both set the direction and influence the subsequent trajectory and pace of innovation, through effective mechanisms of participatory and anticipatory governance. This should be an iterative, inclusive, and open process of adaptive learning, with dynamic capability" (Owen et al. 2013).

One might wonder what an iterative, inclusive, and open process of adaptive learning with dynamic capability would look like; how expensive it would be and how successful it could be. However such questions are related directly to critiques of the definitions themselves. Here we shall simply examine their application in our nanotechnology case study.

Our first two RRI elements (societal needs, societal desirability) are therefore outcome or output based. The innovation output is intended to relate to global societal needs and have the potential to benefit all human beings without discrimination. The third RRI element we are considering, responsiveness, describes the ideal process by which to define what counts as a global societal need, and what counts as benefitting humankind without discrimination.

5.2.3 The Nano-Divide; Societal Needs, Societal Desirability and Responsiveness

Some people predict that nanotechnology will be at the centre of the next significant innovation wave with its ‘revolutionary’ potential in terms of its impact on industrial production (Andreta 2004). One of the main ethical criticisms against nanotechnology is summarized in the term ‘nano-divide’, which has been used since at least 2001 (Yonas and Picraux 2001). It refers to differing access to nanotechnology between low, middle and high income countries. A rather more politically loaded term is ‘nano-apartheid’ (Muchie et al. 2013), which gives an indication of the emotive nature of the ethical debate.

The term nano-divide can be understood in two main ways according to Cozzens and Wetmore (Cozzens and Wetmore 2010). First, the ‘nano-innovation divide’ refers to “inequity based on where knowledge is developed and retained and a country’s capacity to engage in these two processes”; and second, the ‘nano-orientation divide’, which refers to “inequity based on the areas in which nanotechnology research is targeted”. Hence, one use of the term relates to the capacity for nanotechnology development and commercialization, while the other is about the distribution of benefits from its use.

Societal needs, societal desirability (understood as the potential to benefit all human beings without discrimination), and responsiveness are the RRI criteria we selected for a discussion of the nano-divide. The first two RRI criteria we specified focus solely on
Cozzens’ and Wetmore’s second understanding of the nano-divide; namely the targets of nanotechnology. In other words, societal needs and the potential of innovation to benefit all human beings without discrimination are linked to the benefits from the use of nanotechnology. Is research targeted at clean water or improved cosmetics? They are not directly linked to the capacity to undertake nanotechnology research.

Responsiveness, on the other hand, would be required in relation to both understandings of the nano-divide. First, some technologies might not be acceptable to the public in the first place, in which case the required collective reflection would focus on the question of “what futures do we collectively want science and innovation to bring about and on what values are these based?” (Owen et al. 2013) Second, to give direction to individual innovations requires the iterative, inclusive and open process Owen et al envisage when they define responsiveness in innovation. Hence, the three criteria from RRI definitions we chose have the potential to cover the same ground as the debates Cozzens and Wetmore have surveyed for their distinction.

Both understandings of the nano-divide have already been discussed widely in nano-ethics circles. For instance, Celine Kermisch has asked: given that nanotechnology is likely to offer advances in areas of significant benefit to low and middle income countries such as new medicines (better HIV retrovirals is one of her examples), is there a moral obligation to share such life-enhancing technologies? (Kermisch 2012) Note, she does not ask whether to share the outputs of nanotechnology innovation, but the technology itself. In other words, she does not talk about providing access to medicines but about sharing the technology.

At the same time, when the industry itself advertises potential applications, the focus is on the sharing of innovation outcomes rather than technology sharing. For instance, a report from the Nanotechnology Industries Association indicates that use of nanotechnology could transform the remote and poverty-stricken areas of the world with innovations such as water nano-filters, ‘labs on a chip’ that could assist rural doctors, cheaper drugs, batteries that utilise nanotechnology for longer life, improved pesticides and fertilisers, environmental nano-cleansing of contaminated ground, lightweight construction materials that can be transported more cheaply, and better food storage packaging (NIA 2013).

The gap between real-life innovations, and aspirations to develop innovations to assist the under-privileged is often the target of criticism. For instance, it is argued that to date, most nanotechnology innovations have been directed at high-income-world products that are more profitable, such as self-cleaning glass, tennis balls, and cosmetics, and thus nanotechnology has been condemned for its potential to advance Northern consumerism while creating few products aimed at the poor (McKibben 2003). In this context Geoffrey
Hunt asks: “can we at last ... make an international cooperative effort to put nanotechnological developments at the service of human and ecological welfare, or will it be primarily nanotechnology for more over-consumption?” (Hunt 2006) The combination of high-tech innovation potential with possibly enormous societal, medical and environmental impact has always offered an uneasy dilemma for society and specifically policy makers about whether profitability or world societal challenges might be more important (Hermerén 2007).

When approaching the nano-divide from a distributive justice point of view, it has been argued that access to nanotechnology might come to be seen as a right of citizenship, in the same way as access to medical care (Sparrow 2007). “If nanotechnology really is as revolutionary as proponents suggest, then both justice and a concern for the stability of any global political order require that we negotiate the challenges of the nanodivides” (Sparrow 2007).

This summarizes the discussion of the nano-divide from a philosophical perspective. But is there anything instructive one can learn from approaching the nano-divide from an RRI angle? We want to focus on two points.

First, RRI is a research and innovation governance framework on the rise in Europe, developed – amongst others – by the European Commission, the institution which works to improve economic competitiveness, as noted above. Hence, if the same institution was to push both for profitability and addressing societal challenges through innovation focusing on societal needs, the audience reached with information about the nano-divide would probably be larger. In other words, the European Commission might command a larger audience of listeners and readers than the authors of philosophical papers and books. For instance, one could venture that industry is more interested in pronouncements from the European Commission than the arguments of distributive justice philosophers. Of course, one has to note that the European Commission’s own definition of RRI focuses solely on the “needs and expectations of European society” (Science with and for Society - European Commission n.d.) (our emphasis). For the reasons given above, however, this is unjustifiably Eurocentric in a world where innovation governance frameworks have historically been rolled out to the detriment of low and middle income countries and to the benefit of Europe (and other high income

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20 This article does not provide the scope to discuss the concept of justice in detail. For interpretations of different conceptions of justice relevant to international governance frameworks, see (Schroeder & Pogge 2009). Distributive justice is relevant here, as it covers questions of access to technology. Does international distributive justice require the sharing of advanced technologies with less technologically advanced communities in order to improve their prospects, is a typical distributive justice question. Questions of corrective justice could be relevant where the less technologically advanced communities have been harmed by the more technologically advanced communities.
regions). Hence, RRI combined with some basic justice considerations\(^2\) could provide an angle on the nano-divide that comes from an institution known for its focus on economic competitiveness.

Second, if one discusses competitiveness, the nano-divide and RRI in the same breath, one is situated more harmoniously in the middle rather than at either end of another important debate: the benefits and challenges of patents. In terms of a sole focus on competitiveness from a high income country perspective, one would argue that patents rightly bar entry to competitors to “provide the innovator firm with an opportunity to price above the marginal cost and thereby recoup R&D expense” (Danzon and Towse 2003). In terms of a sole focus on the nano-divide, one would stress the access problems of low and middle income economies and related unmet human needs. RRI could be seen as a mediator concept, which tries to combine a concern for competitiveness with a concern for the satisfaction of needs.

The trickle-down effect has often been used to try and marry the concerns of profitability and societal desirability, arguing that what initially benefits the rich, will become available to poorer populations later. In the context of nanotechnology, it is “likely that many of the benefits nanotechnology can provide to the developing world will be delayed by at least a generation or more – the 20-year term of a patent” (Heller and Peterson 2007). Kathy Wetter argues that researchers and innovators in the South are likely to find that participation in the proprietary nanotech revolution is “highly restricted by patent tollbooths, obliging them to pay royalties and licensing fees to gain access” (Wetter 2010). However, a survey of global nano-health patents filed between 1975 and 2004 showed that China owned 20% of internationally filed patents, second only to the US (33%), and ahead of Germany with 13% (Maclurcan 2005).

An example of where nanotechnology research takes place in a lower middle income country focused on a societal challenge is in South Africa, where tuberculosis (TB) is the leading cause of death. Approximately 80% of the population have latent TB, and the incidence of drug-resistant TB is also a major concern (TB Facts n.d.). TB is curable, but only with long drug-courses (6 months for standard TB and 2 years for drug-resistant TB) that are well supervised. Researchers in South Africa are therefore working on a way to incorporate tuberculosis drugs into nanoparticles so that they are released slowly into a patient’s bloodstream, raising the possibility that a regime of daily pills could be replaced by a single weekly dose. Despite the expense of development, “the potential advantages of the technology make its pursuit worthwhile. If TB treatment is reduced to

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\(^2\) A basic justice consideration here would be the Kantian demand not to violate perfect duties. See changes to the international intellectual property rights system (Schroeder 2011) for changes in governance frameworks that predictably led to higher morbidity/mortality in low and middle income countries.
a once-a-week dose, the overall costs, both of the drugs and of employing healthcare staff, could be significantly reduced" (Makoni 2010).

A 2013 Nanotechnology Industries Association Report is optimistic about the resolution of the nano-divide, claiming that:

Nanotechnology is still in its infancy and will take time to deliver on its promises. The developing world will also need time to appropriate the technology so as to make the most out of it and to boost its economies. Global inequality shall not be widened by nanotechnology in and of itself; nevertheless nanotechnology offers a positive influence in reducing the divide between the rich and the poor by providing new approaches to tackle the challenges faced by the developing world, and as such its impact will vary according to how it is implemented (NIA 2013).

Discussing the nano-divide in the context of RRI might broaden the debate by moving from discussions about pure justice to larger RRI discussion circles. Yet the debate could be broadened even more, if innovation systems could be included within it, as these are of prime interest to policy makers and are allegedly descriptive, or non-normative.

5.2.4 The Nano-Divide, Innovation Systems and Inclusive Innovation

As noted above, the Systems of Innovation approach (SI) is the predominant approach by which researchers and policy makers try to make sense of successful innovations which emerge from a whole network of enabling conditions. SI approaches aim to be purely descriptive, or at least without explicit normative elements. By contrast, the nano-divide is a discussion almost exclusively about normative elements. Who should have access to the technology and the outputs of the technology, given that the market will not secure coverage for all those who need it? In this regard the two debates stand at different poles of a spectrum. How could they be combined?

SI research is used by policy makers to steer the system so that innovation can flourish. In this regard, we have a link to RRI. RRI is an approach promoted by policy makers to guide innovation once it is happening, hence one step after SI research helps to analyse the system. However, there is a third area of research interest that could fit into these debates: inclusive innovation. Inclusive innovation combines elements from innovation research with a strong, explicit normative element.

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22 In this article, we do not deal with the normative question of whether the technology should be used in the first place.
Following the Millennium Development Goals\(^\text{23}\) (UN 2002), which sought to improve the economic and social position of the poor, there has been an upsurge of interest in ‘pro-poor’ or ‘inclusive’ growth. Since innovation plays a key role in growth and in determining the character of growth and the distribution of its benefits, increasing attention has been paid to innovation policies and practices that have the potential to assist the poor. The term ‘inclusive innovation’ is now very widely employed. International agencies such as the World Bank have embraced the term, and the United Nations Development Programme (UNDP) maintains an International Policy Centre for Inclusive Growth headquartered in Brasilia, Brazil. A large number of governments, notably in low and middle income countries – for example India and Thailand (Heeks et al. 2013) - have developed or are in the process of developing explicit policies focused on inclusive innovation. The Indian government characterised the 2010-2020 decade as the “Decade of Innovation” and created the National Innovation Council in 2011, with a specific brief to promote inclusive innovation at the national and state levels (Kaplinsky 2013). China’s 12th Five Year Plan (2011 -2015) shifts the focus from pursuing economic growth to sharing the benefits of development with all people and innovation has a key role to play in this. Research organisations, such as the Global Research Alliance, have placed inclusive innovation at the centre of their objectives (Global Research Alliance 2013).

However, there is as yet no agreed definition of the term ‘inclusive innovation’ and indeed there are a variety of similar terms that are employed in different contexts. These terms include: pro-poor innovation, below the radar innovation, bottom of the pyramid innovation, grassroots innovation, and Jugaad or frugal innovation (Horton 2008; Kaplinsky et al. 2009)

What all of these terms have in common is that they refer to the production and delivery of innovative solutions to the problems of the poorest and most marginalised communities and income groups. Some definitions require that the poor are, in some way, actively engaged in the innovation process itself. A broad definition would therefore be: "Inclusive innovation is the means by which new goods and services are developed for and/or by the billions living on the lowest incomes" (Foster and Heeks 2013). In a recent review, Kaplinsky offers the following definition of inclusive innovation: "Inclusive innovations may be new to the sector, new to a country or new to the world and may involve a variety of excluded populations. These innovations may foster inclusion in production, in consumption, in the innovation process itself and by promoting

\(^{23}\) On 25 September 2015, the Millennium Goals were superseded by the UN Sustainable Development Goals. The new agenda consists of 17 goals designed to end poverty and hunger by 2030 (UN 2015).
the agency of the excluded. They may also contribute to environmental and social sustainability” (Kaplinsky 2013).

It is possible to conceive of a number of different levels at which 'inclusivity' could potentially operate:

- a. The poor being engaged in the definition of the problems to be addressed such that the innovation is relevant to the needs of the poor;
- b. The poor being actively engaged in some manner in the development and application of innovative solutions to their problems;
- c. The poor being engaged in the adoption, assimilation and diffusion of innovative solutions to their problems;
- d. The poor being engaged in the impact of innovation such that the innovation outputs maximise the consumption and/or incomes of the poor (Foster and Heeks 2013).

Some protagonists and advocates of inclusive innovation look to the inclusion of poorer people as active participants in the processes of innovation (Cozzens and Sutz 2014). This perspective also defines inclusive innovation in terms of the innovation process and not merely in terms of the outcome. It seeks innovative activity that, in some way, has the potential to enhance the capacities of poor people. As a result, they would not merely be passive recipients of innovation but instead be actively engaged. The active engagement of the poor in the innovation process finds its strongest expression in grassroots or community innovation movements. "Grassroots innovation movements seek innovation processes that are socially inclusive towards local communities in terms of the knowledge, processes and outcomes involved" (Smith et al. 2013).

At first sight, it looks as though RRI and inclusive innovation differ significantly. Inclusive innovation focuses almost exclusively on the needs of the poor, for instance as beneficiaries of innovation or as co-innovators. By contrast, the term 'inclusive' within RRI definitions has no pro-poor focus and is only one amongst many criteria that determine whether research and innovation is undertaken responsibly. For instance, the six key action points the European Commission’s SwafS’ unit has agreed to determine whether research and innovation is undertaken responsibly are: governance, public engagement, gender equality, science education, open access/open science and ethics [2]. Only in one SwafS report have two other action points been added, namely sustainability, and social justice/inclusion (Strand et al. 2015). Hence “inclusion” plays a much smaller role in RRI than it does in inclusive innovation.

However, both inclusive innovation and RRI mirror the above conceptualisation of the nano-divide between innovation for and innovation with end-users. Inclusive innovation
requires the development of new goods and services for the billions living on the lowest incomes whilst also requiring engagement with the poor in the development, adoption, assimilation and diffusion of innovative solutions for their problems. For RRI, the targeting of innovation at societal needs and the inclusion of end-users in innovation processes aims to achieve a better alignment of both the process and the outcomes of research and innovation with the needs of all of society.

If one tried to bring ‘inclusive innovation’ closer to RRI, one could argue that the term inclusion would require that all segments of society benefit from and influence innovation. ‘Pro-poor’ innovation, on the other hand, is a less suitable concept, as it focuses more clearly on one segment of the population only. Whilst one can provide strong arguments for an exclusive focus on the poor, as – for instance – John Rawls did with the difference principle24 in his ground-breaking “A Theory of Justice” (Rawls 1999), RRI definitions focus on the entire population. For instance, the European Commission defines RRI as “an inclusive approach to research and innovation”, as noted above, not one that is focused on the under-privileged. Inclusive innovation is then not about the exclusion of richer populations from innovation and its benefits, but about the broadening of the network positively impacted on by innovation to include all.

Hence, RRI and inclusive innovation can be linked straightforwardly. However, what about the elusive link to the descriptive-only innovation systems approaches? From the brief account given above, we know that innovation systems analysts try to find out, amongst other things, who is involved with which activities in innovation systems. As such, if policies such as RRI or inclusive innovation are successfully realised, innovation systems analysts will find larger, more diverse networks, which also include new actors within their systems. If more population groups and more diverse end-user groups are included, for instance, the innovation system will grow. The important task for Systems of Innovation analysts is then to be sensitive to the pronouncement of RRI and inclusive innovation and its individual components (e.g. societal engagement, gender equality) in order to ascertain whether they improve innovation systems or not. If they can find convincing evidence this would in turn validate the European Commission’s SwafS’ unit claim that RRI is conducive to economic competitiveness.

Innovation systems analysts are important contributors to the RRI debate, as they are best placed to ascertain whether policy maker claims are valid. For instance, does the

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24 The difference principle is based on a simple idea. Given that efforts to achieve full equality in society (which might be regarded as the most just outcome) will invariably lead to systematic and chronic inefficiencies, some inequalities will be allowed, but only if they lead to advantages for the least well off. The difference principle would therefore allow higher salaries for surgeons if it could be shown that their services would not otherwise be available to the least well off.
RRI governance framework indeed increase economic competitiveness? That is a very broad claim. Broken down into smaller claims would probably be more meaningful. Research from innovation systems analysts would then answer questions such as: In which sectors is RRI likely to lead to enhanced economic competitiveness, if any? In which regions is RRI likely to lead to enhanced economic competitiveness, if any? Which role do certain actors play within the innovation system with regards to RRI? As a relatively new concept, RRI needs statistical and case study support for the broad claims it makes, in particular for being able to marry increased social justice (e.g. gender equality, engagement, open access) with increased economic competitiveness. Innovation systems analysts are well placed to provide such data when assessing how responsible research and innovation case studies can be linked to existing approaches (see also Table 1). Likewise, proponents of inclusive innovation need statistical and case study support to ensure that their normative aims are reached.

5.2.5 Conclusion

RRI and inclusive innovation inject moral values into innovation governance systems. Although there is no specific mention of justice in RRI, the implicit framing around justice concepts becomes obvious when one compares nano-divide debates from an RRI perspective and from a traditional philosophical justice perspective. Both approaches can arrive at very similar results. It is undesirable if a technology which has a major potential to improve the lives of the poorest people remains inaccessible to those countries and end-users who need them. Hence, to push for better access to nanotechnology and its innovative outputs, one could use the concept of RRI, enhanced with some arguments from the philosophical justice literature. Given RRI’s pedigree in Europe (namely its development from within the European Commission and therefore its close relationship to economic competitiveness efforts), using RRI pragmatically to push for broader access to nanotechnology and its innovations may give better results than using justice arguments alone.

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25 Thanks to John Weckert and Mary Walker for pointing out this tension.
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5.2.6 References


99


101
5.3 Publication 3: Simulating demand-side effects in innovation

Research questions:

Q4: How can knowledge be modelled in an agent-based simulation in order to show complex behaviour?

Q5: Is ABM a suitable modelling approach for developing policy questions and eventually evaluate them?

With the following publication the aim was to show how knowledge can be modelled using binary strings, how an agent-based simulation model exhibits complex characteristics and how the methodology ABM can applied for policy modelling. Agents representing firms possess pieces of knowledge, which they try to match with the demand of users. This demand is structured in a similar way as knowledge, making it possible to model a matching process. However, if demand cannot be matched, firms try to alter their knowledge. With this agent-based simulation approach, it is possible to show how demand can open up niches for firms, thereby creating the niches in which firms with distinct demand can prosper. This is a fitting example for feedback effects in a complex system represented in an agent based model. Also, diverse demand creates different distributions of firm size distributions, which constitutes an emergent phenomenon at the meso level caused by a micro level behaviour. Finally, the simulation it is demonstrated that the simulation model is suitable for developing and assessing a policy question. The effects of demand side policy interventions are evaluated constructing different policy scenarios.
Authors

Matthias Mueller
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Abstract:
We present an agent-based simulation model of the influence of heterogeneous demand on the innovative behaviour of firms. In our model, firms try to meet the demand of consumers with heterogeneous preferences for product attributes. Introducing heterogeneity into the model leads to a dynamic segmentation of markets and creates permanent and endogenous incentives for innovation and knowledge creation. The first striking result is that heterogeneity itself creates an out-of-equilibrium dynamic where no steady state is achieved: already a small deviation from perfect homogeneous demand creates a segmentation of markets with varying niches which opens up the market for a large number of firms. Second, different degrees of consumer heterogeneity can create log-normal as well as normal distributions of firm sizes. Finally, simulation experiments indicate the impact of different policy strategies designed to foster innovation. In a situation where existing products do not meet consumer demand supply side subsidies are only suitable under certain circumstances and may eventually cause major drawbacks.

Keywords: Innovation and demand, Neo-Schumpeterian Economics, Agent-based Modelling, Recombinant Knowledge, Heterogeneity, Innovation policy.
5.3.1 Introduction

In its Horizon 2020 strategy the European Commission (2010) highlights the goal for smart, sustainable and inclusive growth for Europe. Undoubtedly this implies a pivotal role of innovation while at the same time acknowledging societal and consumer needs. This policy agenda has clearly refrained from the sequential view on the innovation process. Instead, this view has been replaced by a more comprehensive view in which the different phases of the innovation process strongly overlap and feedback into each other as different and heterogeneous actors strongly interact in all phases of the innovation process and on both sides, i.e. the supply side and the demand side, of the market.

In this paper we contribute to the discussion on the role of demand in the innovation process by developing an agent-based model of an economy in which a heterogeneously composed demand side is facing an experimentally organized supply side (Eliasson 1991). Heterogeneity of demand often is modelled via heterogeneously distributed adoption thresholds to approximate varying propensities to adopt a new technology (Kiesling, Günther, Stummer and Wakolbinger, 2012). In other important approaches heterogeneity of demand is generated via reservation prices (Cantono and Silverberg 2009), communication behaviour (Rahmandad and Sterman 2008) or socio-demographic characteristics (Dugundji and Gulyás 2008). Inspired by the work of Kelvin Lancaster (1966, 1990), however, the proposed simulation model incorporates heterogeneity of demand from consumers having individual preferences for the peculiarities of product characteristics (e.g. the particular colour or size of a product). This individual concept includes a full image of a preferable product concerning the shaping of all possible product characteristics. With this we aim at introducing a general model of interaction between heterogeneous producers and heterogeneous consumers in an environment where producers are forced by the innovative activities of competitors to continuously adapt to market conditions.

To broaden our understanding of the effects of heterogeneous consumers, in our analysis we focus on the effects of different levels of consumer heterogeneity. Our starting point is a standard scenario, which aims to show the fundamental impacts of consumer heterogeneity on economic dynamics and processes. For this purpose we focus on the effects of heterogeneity of consumers, varying consumer preferences on a spectrum between full homogeneity and full heterogeneity and analysing the innovation behaviour of firms and the resulting market structure. In a second experiment setting, the simulation model is used as a test laboratory for in-silico-experiments, investigating the impact of different policy strategies designed for fostering innovation.
The paper is organized as follows: In section 5.3.2 we briefly outline relevant aspects of the demand side considered in the literature so far and describe the basic concepts of product and knowledge representation in our model. Section 5.3.4.1 starts with a detailed model description and, subsequently, in section 5.3.4.2 we discuss the results of the two simulation experiments already mentioned. Finally, conclusions and a critical appraisal are presented in section 5.3.5.

5.3.2 Conceptual framework

5.3.2.1 The neglected demand side

Many authors have argued that demand side effects on the innovation processes has been neglected or disregarded over the last decades (Witt, 2001; Coombs, Green, Richards, and Walsh, 2001). More specifically, Adner and Levinthal (2001) note that by far the larger portion of work on technological change is concentrated on supply side dynamics. Harvey et al. (2001) stress the myopic concentration on the terms of market exchange characteristics of innovation studies, with its excessive attention to supply side processes. However, it would be false to postulate that the demand side and the role of the consumer has not been considered at all.

Although one could argue that even long before Adam Smith, demand has been considered in economics (Knell 2012), it was not until the seminal work of Jacob Schmookler (1962, 1966) that the demand side has been (re-) recognized as one of the key factors of economic development. Unsatisfied with the linear view of a supply-oriented focus on the innovation process, Schmookler (1962, 1966) shows, by studying different industries of the US economy, that peaks in patenting activities lag behind peaks of output of commodities. He concluded that the influence [upon innovation] of the latter [unfolding economic needs] has been substantial, at least in established industries (Schmookler, 1962, p.20).

Since then, a series of empirical studies have tried to support the hypothesis by Schmookler (Andersen 2007) while others viewed the activities and internal capabilities of firms as the primary drivers of innovation (Dosi 1982b). As a preliminary result of the debate between demand and supply arguments both the demand and the supply side appear to simultaneously play crucial roles (Mowery and Rosenberg, 1979; Dosi, 1982). Successful innovation emerges from the interaction between demand-pull and technology-push effects (Mowery and Rosenberg 1979).

The debate between the demand side and supply side perspective has, however, not vanished as e.g. Andersen (2007) points out. Instead, it has branched out into a number of sub-debates, each highlighting different aspects of demand in the innovation processes. While many of the earlier studies were focussed on the effect of demand
growth on the innovative activities of firms, in recent years a number of evolutionary models have extended the scope analysing the relevance of different demand side aspects and the effects on their innovative process (see for example Andersen (2001); Saviotti (2001); Metcalfe (2001); Saviotti and Pyka (2004); Valente (2012) for important contributions).

Following the work of Lancaster (1966, 1990) products in our simulation are characterised by a set of characteristics forming a multidimensional characteristics space which consumers can perceive and are fully aware of. In the following analysis we mainly focus on the effects of different degrees of heterogeneity of consumer demand. This of course does neither represent a comprehensive picture of the demand side nor does it include other major drivers of the innovative processes. Our aim, however, is to understand the fundamental processes occurring within a heterogenous demand environment showing the differences and basic implications of considering heterogeneous consumers in an neo-Schumpeterian fashioned simulation model.

5.3.3 Key ingredients: knowledge and products

One key element for broadening the research object is a proper representation of knowledge, products and preferences and the respective coding in the model. Following Gilbert et al. (2001; 2007) we begin with an abstract characterisation of knowledge by assuming knowledge of a firm $i$ to be a set of single knowledge units (KU). The knowledge endowment $K^i$ a firm possesses is represented in three knowledge units $KU_i$, each of them being a ten digit binary string of code (Equation 1):

$$K^i = \left\{ KU_1^i \text{ e.g. } 1010110000, \ KU_2^i \text{ e.g. } 0010000000, \ KU_3^i \text{ e.g. } 1101100001 \right\} \quad (1)$$

This set of knowledge units defines the product a firm is producing including all information about the product, i.e. the product category and product characteristics. Accordingly, we need to define unique functional relationships determining a particular product characteristic $C_{c,g}^{S,i}$, which is also a bit string, with superscript $S$ indicating a characteristic from the supply side, index $c$ specifying the number of the characteristic and $g$ indicating the product category, based on the individual knowledge stock of a firm $K^i$ (Equation 2).

$$C_{c,g}^{S,i} = f (K^i) \quad (2)$$
Describing the knowledge units as binary bit strings allows for the definition of a unique mapping function $M_{c,g}$ for any product characteristic $C_{c,g}$ within a product category $g$. These mapping functions contain the information on how to read out the knowledge from equation (1) in order to compute a products' characteristics $C_{c,g}^S$. The characteristic itself is then represented as a similar bit stream of ten digits. The mapping functions contain a list of randomly defined positions determining which bit of which knowledge unit in a firm’s knowledge is relevant for the characteristic. The following example illustrates how product characteristics are defined:

The knowledge endowment of a firm as in equation 1 is read out according to the mapping function $M_{1,1}$ in (3) in order to obtain characteristic 1 of products of category 1:

$$M_{1,1} = 1,1,1,2,2,2,3,3,3$$  \hspace{1cm} (3)

Hence, the following bits (bits underlined) are relevant (4) for the product characteristic $C_{1,1}$ of the product of this firm:

$$K^i = \begin{bmatrix} KU_{1,e.g.} & 1010110000 \\ KU_{2,e.g.} & 0010000000 \\ KU_{3,e.g.} & 1101100001 \end{bmatrix}$$  \hspace{1cm} (4)

Which defines the product characteristic $C_{1,1}^S$ as follows (5):

$$C_{1,1}^S = 1010000001$$  \hspace{1cm} (5)

Working with mapping functions as ‘instructions’ on how to read out the available knowledge holds the advantage that it is possible to easily obtain a large number of products with several characteristics from a very limited number of mapping functions. At the same time, this keeps the mapping process flexible in a sense that a change in the underlying knowledge may result in different products without having to change the mapping functions. This is particularly true if we consider a multidimensional knowledge space and a flexible product characterisation as follows: First, knowledge is at least partly substitutive meaning that the use of different knowledge stocks may eventually lead to the same product characteristics. Second, the functions should be able to reproduce possible interdependences between some characteristics, e.g. it is hard to produce a product which is robust and lightweight at the same time. Third, the functions need to be transparent as well as variable and computational.
Acknowledging these traits we randomly generate the mapping functions initialising the simulation. Each mapping function is randomly assigned to a characteristic of a product category.

Illustrating this we exemplary define equation 6 as a second mapping function:

\[ M_{2,1} = 3,3,3,2,2,2,1,1,1 \]  

(6)

This then leads to the product characteristic \( C_{2,1} \) (i.e. the second characteristic of the first product category) as (7):

\[ C_{2,1}^{5,i} = 110 \ 0000 \ 101 \]  

(7)

As a consequence, successful innovation i.e. a change in the knowledge space (equation 2) can lead to

- no changes, if the respective part of the knowledge bit stream is not included in neither of the mapping functions of the respective product and its characteristics,
- a change of only one characteristic, if it is included in only one mapping function, and
- a change of more than one characteristics, if it is included in the respective mapping functions.

Given a change of more than one characteristics this mechanism does explicitly include the possibility that these changes do not fit together, hence the change in one characteristic will bring this respective characteristic closer to the consumer’s need while at the same time driving away another characteristic of the same product from the consumer’s needs.

5.3.4 The simulation model

5.3.4.1 Model Description

In a nutshell our simulation model can be described as the numerical description of the adaptation process of profit-driven firms trying to sell their products to heterogeneous consumers characterised by individual demand. On the supply side the processes are as follows: Each time step firms try to sell their products to consumers with each product being characterised by a number of product characteristics and a number indicating the product category. Based on market returns, firms decide to engage in research and development, i.e. to innovate by changing their knowledge stock.
For initialising the simulation is populated with a random number of firms and consumers. Each firm is endowed with a random set of three knowledge units (see equation 4 for an example) and each consumer is equipped with demand for a fixed, individually optimized product. This representation of product characteristics (see section 5.3.2.2) is also used to equip consumers with individual preferences concerning these characteristics in a similar way also as bit streams. More precisely, each consumer $n$ is assigned a product concept $D_n$ including the product category $g$ and all possible demanded peculiarities of product characteristics (see equation 8). This can be interpreted as an individual preference for example for a certain size, colour or functionality. We use the superscript $D$ in order to indicate the characteristic is based on the demand of the consumer rather than on the supply of the firm.

$$D^n = \begin{cases} c_{1,g}^{D,n} & e.g. 1110110100 \\ c_{2,g}^{D,n} & e.g. 0011010010 \\ c_{c,g}^{D,n} & e.g. 1101100001 \end{cases}$$

In order to model the full spectrum between homogeneity and full heterogeneity the parameter $p$ describes the degree of heterogeneity of consumers’ demand. We start with a homogeneous market in which all consumers follow a global standard (i.e. share the same preference for characteristic peculiarities within a product category). The parameter $p$ defines the probability for any bit of a consumer’s set of desired product characteristics $D_n$ to differ from the global standard for the respective product category. With this we can easily switch between the two extremes: homogeneous markets ($p = 0$; i.e. all consumers follow the standard) on the one hand and fully heterogeneous markets ($p = 1$) on the other hand where every consumer has its individual product in mind which he or she wants to buy. Also in-between degrees of heterogeneous markets (e.g. $p = 0.5$ where on average 50% of the digits of consumer preferences are individual) can be analysed. Heterogeneity of demand in this sense, as specified by the probability $p$, referrers to the variety of consumer desires. In contrast to most textbook demand representations where purchasing decisions are often made solely based on prices, in our model consumer demand has a multi-dimensional character, complicating the innovative efforts of producers.

Finally, during the initialisation phase mapping functions are generated randomly (see section 5.3.2.2). More precisely, the simulation creates $c$ times $g$ functions to determine every possible product characteristic $c$ within a product category $g$. Additionally, the simulation creates one (global) mapping function to determine the specific product category a firm’s product is assigned to. For this, we simply compute the decimal value of the resulting bit string and divide it modulo the total number of product characteristics.
The routine for the rest of the simulation is implemented as follows:

- Each firm produces a product based on its individual knowledge stock
- Consumers analyse all products available, purchasing the product best matching the consumers’ preferences
- Firms engage in R&D in accordance with their innovation strategy
- Firms without sales for more than five periods are deleted from the market and a constant number of new, randomly generated firms enter the market

To give an example of how a firm’s product is defined and how consumers evaluate products, let us assume a random firm \(i\) to be endowed with the following knowledge stock (equation 9):

\[
K^i = \begin{cases} 
0110011011 \\
0010001111 \\
1010101100 
\end{cases} 
\]  

(9)

Furthermore, let the mapping function to define the product category \(M_G\) be:

\[
M_G = 1,1,1,2,2,2,3,3,3 
\]  

(10)

This leads to the temporally bit string:

\[0110001100\]  

(11)

Written in decimals this bit string equals 792, which then defines the product category 2 considering 10 possible product categories (792 modulo 10 = 2).

Finally, let us assume that products are characterized by two product characteristics and the respective mapping functions \(M_{1,2}, M_{2,2}\) define the product characteristics \(C_{1,2}^S, C_{2,2}^S\) as:

\[
M_{1,2} = 2,2,2,1,1,1,3,3,3 \quad M_{2,2} = 3,2,1,2,3,2,1,2,3,2 
\]  

(12)

\[
C_{1,2}^{S,i} = 0010011100 \quad C_{2,2}^{S,i} = 1010101101 
\]  

(13)

Obviously, a full fit between a product \(P_i\) offered by a firm \(i\) and the product \(D_n\) desired by a customer \(n\) can only rarely be observed. In order to determine the fitness between the products offered and the consumer demand the Hamming distance (Hamming 1950) is applied; i.e. first it is determined on how many positions over all characteristics of the product the product offered differs from the product desired. This number is then divided by the maximum number of digits.
Equation 14 shows a simple example on how the compatibility between a consumer’s demand and a firm’s offer is determined. In this example the eight underlined bits match the demand of the consumer. In total there are 20 bits, this leads to a level of compatibility of 40%.

\[
\begin{align*}
p^i; \left\{ \begin{array}{ll} 
C_{1,1}^S & = 0010011100 \\
C_{2,1}^S & = 1010101101 
\end{array} \right\} & \Rightarrow \left\{ \begin{array}{ll} 
C_{1,1}^D & = \text{e.g. } 1110110100 \\
C_{2,1}^D & = \text{e.g. } 0011010010 
\end{array} \right\}; D^n \quad (14)
\end{align*}
\]

Based on this evaluation consumers buy the, in their opinion, best product. In case two products feature the same level of compatibility, consumers choose randomly.

In a next step, firms decide about their R&D strategy. A firm’s engagement in R&D is based on two criteria, both of which are conceptualized as thresholds within the firms’ decision routines (Nelson & Winter 1982). First, we define a firm’s market share \( S_i \) as firm \( i \)’s share of consumers having demand for products in the respective product category of firm \( i \). If the market share is low (below the threshold for radical research \( h^r \)) the firm will engage in radical R&D. This means that a firm is deleting one of its knowledge units entirely replacing it with another knowledge unit randomly chosen. Radical R&D therefore can be interpreted as the attempt of a firm to search for new market niches since the potentially new characteristics will be perceived very differently on the consumer side. Furthermore, for cases in which the firm’s market share is above the radical threshold but still below the threshold for incremental research \( h^i \) the firm will engage in incremental R&D. The respective firm only changes one bit of one of its randomly chosen knowledge units thereby trying to more successfully adapt to the needs of consumers in an existing market niche. With a firm’s market share being high enough (i.e. above the incremental threshold) the firm no longer engages in R&D. This means that the respective firm is satisfied with its market position avoiding the risk of possible negative consequences of modified knowledge about the characteristics of its products.

Finally, our model reflects Schumpeterian competition based on innovation, leading to creative destruction by allowing for entries and exits. We assume that each time step a constant number of new firms enters the market in an entrepreneurial fashion. Simultaneously, firms are forced to exit the market if they are unable to sell their products for more than five consecutive periods.

5.3.4.2 Simulation Experiments

The following description of our simulation results is subdivided into two experiments: First, in a standard scenario we stress the dynamic effects of innovation caused by increasing heterogeneity of consumers. With this we aim to show the fundamental
dynamics caused by covering the fact that products are more than goods which can be characterised only by price and quality.

In a second experiment we show a possible application of our model investigating the impact of different policy strategies intended to foster the performance of an economy via innovation.

- **Analysing the effects of heterogeneous agents on the demand side**

In our first scenario we use the following parameter setting and initial values displayed in Table 4. Unless otherwise stated the simulation is run 1000 times to minimize aberrations due to random effects.

<table>
<thead>
<tr>
<th>Parameter:</th>
<th>Parameter:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of consumers</td>
<td>100</td>
</tr>
<tr>
<td>Initial number of firms</td>
<td>10</td>
</tr>
<tr>
<td>Number of product categories</td>
<td>10</td>
</tr>
<tr>
<td>Digits of a knowledge unit</td>
<td>10</td>
</tr>
<tr>
<td>Market share for incremental R&amp;D</td>
<td>&lt; 30%</td>
</tr>
<tr>
<td>Digits of a product characteristic</td>
<td>&lt; 10%</td>
</tr>
<tr>
<td>Product characteristics</td>
<td>2</td>
</tr>
<tr>
<td>Market share for radical R&amp;D</td>
<td>&lt; 10%</td>
</tr>
</tbody>
</table>

Table 4: Parameters and initial values of the first experiment

Figures 21a and 21b depict two experiments analysing the average number of firms in 1000 simulation runs as well as the average level compatibility (i.e. fitness) of offered products with the individual product demand of consumers, each measured after 500 iterations for different values of heterogeneity (\(p\)).
Our starting point is a market in which all consumers share the same concept regarding the product characteristics \((p = 0)\) i.e. where firms are confronted with homogeneous demand. Resulting from perfect information on the demand side firms are subdivided into market-leaders, serving the entire market with their products and firms without sales. Subsequently, the latter engage in radical R&D trying to find new knowledge units until they are either capable of producing a better product than the market leaders or they exit the market. This process continues until one firm finds a product, which fits entirely to the homogeneous demand and a stable market equilibrium is achieved, which in turn reduces the incentives for firms to innovate.

Increasing variety of preferences (introduced by the probability \(p\)) creates a situation where firms sell their product in small niches composed of similar consumers because no other firm will be able to meet the preferences of all consumers. As a result heterogeneity creates segmented markets with an overall larger number of firms (fig. 21a). Because of the diversified R&D efforts we also find a (slightly) smaller average level of compatibility from a consumer perspective (fig. 21b). This is despite the more difficult initial situation concerning the heterogeneous preferences indicating a relative good fit between desired and produced product characteristics achieved by the R&D processes of firms.
In accordance with the segmentation of consumers in niches the distribution of sales varies depending on the degree of heterogeneity. For investigating the market structure in more detail figures 22a, b, c and d show the histograms of sales for different degrees of heterogeneity, measured after 500 steps, for 1000 simulation runs for all product categories. Starting with a homogeneous demand (figure 22a), the market shows a clear division in market leaders (serving 100% of their market niches), unsuccessful firms with no sales and a few firms with sales which cover e.g. 50% of their market niches in the case they share their market niches in a duopoly with another company offering the same product.
Increasing heterogeneity creates a entirely different picture. As we can see in figure 19b, already small differences in consumer preferences \((p = 0.4)\) leads to a more balanced distribution of firms’ market shares (see for example Valente 2012 for similar results) with a high number of firms with no or only few sales and a moderate number of firms with 30% of all sales or more. For \(p = 0.6\) and \(p = 1\) the situation changes and the distribution of sales approximates a right-tailed log-normal distribution for \(p = 0.6\) and a standard normal distribution for \(p = 1\) (see also figure 23a and 23b for the QQ-plots taken from single exposures for one product category of a single simulation run).

Our results indicate that heterogeneity on the demand side and the resulting segmentation of the market may account for observed firm size distributions. Also, the approach presented may suit as an alternative for so far dominant stochastic models in this field. This is of particular interest with respect to the discussion in literature on the distribution of firm sizes and firm growth rates (Cabral and Mata 2003).
Fig. 23: QQ-plots for a lognormal distribution (p=0.6) and normal distribution (p=1)

With our standard scenario we analyse the dynamic effects immediately relevant when allowing for heterogeneous demand. While the situation in a homogenous market with one technological leader seems to be static at least for a short period of time our results show that heterogeneity creates highly unstable dynamics with varying but endogenous incentives to innovate. Instead of creating a situation in which technological leaders for several fixed small niches become established we find a persisting dynamic situation in which firms are unable to occupy stable market shares. Since even for a small niche a full match between products supplied and demanded is highly unlikely there is always the chance for competitors to entice customers. This in turn is a constant challenge to the firms involved in that niche and they are forced to engage in R&D activities to regain their market shares which then may entice consumers from other niches in turn forcing
other firms to engage in R&D. As a consequence, heterogeneity on the demand side creates, if not hindered by other factors and processes such as incomplete information about products or unreasonable loyalty to producers or products, incentives to innovate endogenously.

Although the focus of the analysis was laid on the heterogeneity parameter $p$, other parameters of the system, such as the size of the market indicated by the number of consumers or the size of the characteristic space created by the length and number of product characteristics also show strong effects on the outcome of the simulation. As our results indicate the dynamic segmentation of consumers requires a sufficient number of both, consumers as well as products showing a sufficiently large number of distinguishing characteristics for segmentation to occur (Figure 24).

![Fig. 24: Number of Firms depending on the market size and the length of the characteristic space](image)

Given a sufficiently large market the size of the characteristic space as expressed by the number of product characteristics and the length of the characteristic bit string determines the possible number of segments. In markets where products are only characterised by a small number of characteristics, as for example the market for energy (or if consumers’ perception of the characteristic space is limited) firms will not be able to differentiate their products from competitors. This in turn will decrease the number of possible segments and hence will limit the innovative efforts of firms to occupy niches. A sufficient size of the characteristic space however, is not a sufficient condition for market segmentation to occur. While in a homogeneous market the number of consumers is irrelevant for the creation of niches, the segmentation of markets induced for example by the heterogeneity of consumer demand must be sustained by a sufficient
number of consumers. Determined by the innovation strategies, which will be the focus of the next scenario, a single niche requires a minimum number of consumers, otherwise firms in the respective niche will try to alter the product to entice new customers.

- An application: Policy experiments

Finally, we apply our model to illustrate its usefulness for policy experiments. So far we have assumed consumers to accept the best offer regardless of the individual levels of compatibility. For the following experiments we implement an additional threshold $k$ defining the minimum level of compatibility necessary to trigger sales. For instance, for $k = 70\%$ a product needs to fit at least with 70% of consumers’ preferences or the consumers will decline the offer i.e. will not buy a product in this period. In order to show the impact of a market with sensitive consumers, Figure 25 depicts the resulting performance of the economy measured in the number of firms after 500 periods for different levels of $k$ and two different R&D strategies.

This experiment aims to find out how policy interventions aiming at the creation of a new industry may influence the number of firms. In particular, this experiment is suited to analysing the different impacts of policy instruments targeting either the supply- or the demand side. Within our simplified model one possible effect of supply-side subsidies can be seen as switching from a high R&D threshold to a low R&D threshold. Subsidies in this sense support firms in the market financially and hence reduce the minimum number of consumers necessary below which firms try to change their product by innovation. Contrastingly demand-oriented policies designed to trigger the development in a new industry sector could be targeted at influencing the customers’ decision by decreasing the minimum level of compatibility. Purchasing innovative goods could be triggered by price subsidies, increasing the probability of purchasing these goods despite a low fit with desired characteristics.

In the following experiment we compare the development of the number of firms in these two scenarios.
Figure 25 shows for both R&D strategies that given a high $k$ new markets fail to emerge. For $k$ between 55% and 80% the effect of a lower threshold for research, measured as the difference between both curves (i.e. the two R&D strategies) is positive. For $k < 55\%$ the effect reverses and a higher R&D threshold creates an economy with a higher number of firms.

The reason for the economy to fail for a high $k$ under both R&D thresholds could be that firms find themselves unable occupying niches containing a satisfying number of consumers, because (a) the firms’ expectations about the niche size are too high or (b) the high level of $k$ hinders the pooling of consumers to a niche where one product can satisfy the preferences of different consumers.

Our results indicate that if consumer preferences are heterogeneous and $k$ is high a good match with one consumer’s preferences renders it almost impossible to match other consumers’ preferences. Hence, in this case the R&D threshold would have to be decreased to a point where already a niche of one consumer would be acceptable for the firm to stay in the market. From a policy perspective this would mean that an intervention would be ineffective. In contrast to this we see that subsidising the consumer side and decreasing the minimum level of compatibility opens up the market so that small niches can emerge.

For $k$ between 55% and 80%, we find a situation showing a number of small niches (of varying size). Again, subsidising the demand side could increase the number of firms although in this situation reducing the minimum number of consumers necessary (i.e. reducing the R&D threshold) can also effectively increase the number of firms.

For low values of $k$ the positive effect of supply side subsidies reverses. As pointed out above, a market with heterogeneous consumer preferences produces fluctuations in
firms’ market shares. As a result, already a small niche can provide enough reward for a high number of firms to stay in the market. Reducing the R&D threshold however, limits these dynamics and consequently reduces the number of firms in the simulation. Although both parameters (R&D threshold and minimum level of compatibility) represent abstract concepts they are suited for an interpretation from a short-term policy perspective. As discussed above one possible policy measure to influence this required level can be found in subsidies on the consumer side. Secondly, subsidies could also be seen to affect firms’ R&D strategies if for example the research and production costs of a firm are subsidized. This decreases the minimum market share, which is considered to be necessary. Eventually, one could interpret the results in Figure 25 as follows: Starting at a point where our simulated economy fails to support the emergence of a new industry \((k > 80\%)\), we see that firm oriented subsidies affecting the R&D strategy do not have an effect on the emergence of the industry. Within the range of \(k\) between 80% and 55%, however, subsidies for firms can have a positive effect although the results don’t indicate whether these subsidies are more efficient than demand-side subsidies, which also have a positive impact. This positive effect on the number of firms however, reverses again with smaller compatibility rates \((k < 55)\).

As a result of this experiment we claim that a sound design of innovation policies to foster industry development has to consider both sides of the market and to carefully evaluate which market side should be influenced by policy interventions.

5.3.5 Conclusions and outlook

In this paper we introduce an agent-based model of innovation, knowledge creation and demand. Innovative firms try to adapt their knowledge stock through R&D to fit the individual preferences of consumers. In contrast to existing approaches our model incorporates heterogeneity of demand as the individual preferences for product characteristics such as for example colour, size or functionality.

The first challenge was to find an adequate representation of knowledge and a suitable and flexible method to transform knowledge into marketable products and the corresponding environment. With our approach of a knowledge representation as bit sequences and with the use of mapping functions we can implement a coding of knowledge to products which represents substitution, interdependence, transparency which is variable and computational.

While the processes introduced may be considered simplistic they are nonetheless able to regenerate fundamental processes, which have to be considered. The first striking result is that consumer heterogeneity itself creates a persistent dynamic beyond any equilibrium consideration without reaching a steady state. Already a small deviation from
perfect homogeneous demand creates varying niches, which open the market for a high number of firms. The firms find themselves in a highly competitive situation, which creates constant and endogenous incentives for innovation and knowledge creation. In this situation every temporary stable market can easily be destroyed by the innovation activities of competitors or market entrants.

Second, the simulation models is capable of showing that log-normal as well as normal firm size distributions can be explained by the heterogeneity of consumers. Since the findings of Robert Gibrat (1931) several authors have looked at the firm size distribution (FSD) and received widely shared stylized fact is that the FSD is stable and approximately log-normal (Cabral & Mata 2003). Recent empirical evidence shows that the FSD in more complete data sets may evolve over time and differ from a lognormal distribution (Evans, 1987; Hall, 1987; Cabral & Mata, 2003). In this context our model places the heterogeneity of demand into perspective. Having in mind the findings of Cabral and Mata (2003) that the FSD in more complete data sets evolve over time from a log-normal to a normal FSD may lead to the hypothesis that a possible explanation for this is an increasing level of heterogeneity and differentiation in the respective markets. Finally, our modelling environment allows for so-called in-silicio-experiments to find out the impact of different policy strategies designed to foster innovation. For this purpose we analyse the differences in the effectiveness of demand-side vs. supply-side subsidies in a situation where the existing products cannot satisfy consumer demand. We show that within our simplified model supply side subsidies are only suitable under certain circumstances and may eventually cause major drawbacks.

Obviously, the simplistic model presented allows for a wide range of improvements and applications. One opportunity for future research is to concentrate on the analysis of the knowledge space. So far, the emerging structures in the knowledge space are random although one may expect them to follow regularities created by the interdependence between the research activities of firms. A second task for future research is the in-depth analysis of the effects of dynamic demand on innovation and knowledge creation in order to detect possibilities for demand side policy instruments to intervene successfully in economic development.

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5.3.6 References


5.4 Publication 4: Modelling the emergence of a general purpose technology from a knowledge based perspective – the case of nanotechnology

Research questions:

Q6: What are the indicators needed to identify GPTs in the SKIN model?  
Q7: Do GPTs already emerge or disseminate within the SKIN model?

The SKIN model is a widely used simulation platform for policy modelling based on the theories stated in Chapter 2 (Ahrweiler et al. 2016). For capturing even more complex characteristics of knowledge as compared to the simulation approach in Chapter 4.3, the SKIN platform is selected. Most importantly the relations and the relation dynamics between pieces of knowledge are of interest here, as the results can be validated against the findings of the empirical study in Chapter 5.1. In the following, first, a number of indicators based on GPT theory is developed for identifying possible GPTs in the SKIN model. The indicators are then applied in the simulation and results are checked whether they reveal the existence of GPTs within the simulation. It turns out that the SKIN model is unable to reproduce GPTs without changes. The publication concludes with outlining possible adaptations to the SKIN model in order to simulate the emergence and/or diffusion of GPTs.
Authors

Benjamin Schrempf
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Abstract

Nanotechnology, the manipulation and control of matter at the scale 1–100 nm, proves to have an increasing socio-economic impact on its way to become the key-technology of the twenty-first century. It has already found applications in various industrial sectors such as information and communication technology, pharmaceuticals, materials and manufacturing, or biotechnology. Nanotechnology is a so-called "General Purpose Technology (GPT)"; with a broad range of applicability and spread in many industries, its innovation networks considerably differ from those of other emerging technologies. Having a strong semiconductor, materials, and biotechnology industry, the highest "Revealed Technological Advantage" in nanotechnology of Western Europe, and a high share of nanotechnology patents, Ireland seems to be a promising case study for investigating the dynamics of nanotechnology knowledge, its role in the economy, and the effect of policies on both. In this paper, we address the specific characteristics of GPT innovation networks and suggest ways to model them using Ireland as an empirical case study. We discuss literature providing important stylised facts about nanotechnology/GPT and suggest how they can be implemented into a SKIN application simulating Irish nanotech innovation networks.
5.4.1 Introduction

Nanotechnology as scientific field already has a strong impact on the socio-economic development of the economy and will have even more so in the future, making it ‘the key-technology of the 21st century’ (Bhattacharya and Shilpa 2011). It is often defined as the manipulation and control of matter at the scale 1-100 nanometres with applications to be found in numerous sectors such as the information and communication technology industry (ICT), pharmaceutical industry, material and manufacturing industry or biotechnology.

The analysis of nanotechnology science and technology, research and innovation has been of huge interest in recent years, investigating nanotechnology specific characteristics for instance of knowledge generation and diffusion, the scope, structure and dynamics of the field, its interdisciplinarity as well as its impact on the economy and the management of nanotechnology research and innovation. With nanotechnology being widely regarded as a general purpose technology (e.g. Teichert 2012), nanotechnology patterns differ in many aspects from other emerging technologies not showing a comparable broad range of applicability. As knowledge is one major prerequisite for innovation, the investigation of its generation, structure and dynamics are of great importance. Taking a knowledge perspective on the emergence of nanotechnology therefore seems to be appropriate in order to understand how nanotechnology may evolve thereby influencing the economy. The insights gained can help policy makers to design efficient policy measures for fostering knowledge generation, make use of synergies and commercialise the knowledge in form of inventions, thus generating economic output.

In this contribution, we describe a number of stylised facts from literature and empirics on the emergence of general purpose technologies (GPTs) in general and nanotechnology in particular. A number of indicators characterising a GPT are identified and applied to the SKIN model. This is to investigate whether GPTs can already be found emerging within the simulation model. With our work we contribute to the literature of GPTs by modelling the emergence and diffusion of GPTs within networks from a knowledge perspective.

The empirical data used is based on a case study on the Irish nanotechnology sector. With a strong semiconductor, materials and biotechnology sector (Forfás 2010), the highest revealed technological advantage in nanotechnology in western Europe (OECD 2009) and a rapid growth and high share of nanotechnology patents, Ireland provides a promising sample to study the dynamics of nanotechnology knowledge, its role in the economy, and the effect of policy measures on nanotechnology evolution.
The remainder of the paper is organized as follows. Section 5.4.2 will give a short introduction to the literature of general purpose technologies and existing models. Subsequently, it is discussed whether nanotechnology can be considered a GPT and why we need distinct GPT models. Section 5.4.3 identifies stylised facts a meaningful GPT model should be able to replicate. Looking at several different indicators the SKIN model is examined with respect to two of the most important characteristics. Additional measures for the GPT features remaining are introduced and proposals for an improved knowledge and value chain representation are given. Section 5.4.5 concludes.

5.4.2 General purpose technologies

5.4.2.1 GPT literature

The term general purpose technology was coined by Bresnahan and Trajtenberg (1995) who define GPTs as ‘characterized by pervasiveness, inherent potential for technical improvements and ‘innovational complementaries’.’ (p. 83). GPTs are also said to play a major role in economic growth: by incorporating them in economic models it is possible to explain growth endogenously and provide an integrated model of growth and business cycles (Bresnahan and Trajtenberg, 1995). In the literature, the term ‘enabling technologies’ is often used similarly and refers to the character of GPTs: combined with other technologies of the application sectors, the emergence of GPTs triggers innovations (Bresnahan 2010).

According to Schiess (2011) the literature on GPTs can be classified in two main strands: The first strand mainly deals with the invention of GPTs, the second strand with their diffusion. Models focussing on the invention of GPTs can be further divided into models that emphasize the connection between R&D efforts and growth triggered by the emergence of one or more GPTs, and models that underline the need for complementary innovations in order to make use of the GPTs. Both strands rather focus on the explanation of long-term growth whereas lifecycles (of both, the GPT as well as the application technologies) are not taken into account. In the complementary-focussed models the diffusion of a GPT is determined significantly by the complexity of the complementaries to be developed for the application of the technology (Bresnahan 2010) and might differ from AS to AS.

Literature on the diffusion of GPTs either deals with domestic diffusion or sectoral diffusion characteristics, thereby focussing on the s-curve shaped pattern of diffusion. Other models apply a North/South framework, emphasising relative productivity differences. Most of these models mainly try to explain the productivity paradox – the empirical fact that productivity slows down in the early phase of the advent of a new GPT. This phenomenon was first described by Robert Solow (1987), referring to the
developments after the introduction of computers in the economy, which did not lead to higher productivity. However, several years after the introduction productivity and growth rates rose again. The same effects could be identified for other GPTs. These models are therefore attempting to explain more short-term waves of growth (as first described by Kondratiev) by the emergence of one or more GPTs (Bresnahan, 2010; Schiess, 2011). The models not only differ in endogenous emergence of the GPT or an exogenous GPT shock, but also in how GPTs are replaced. Some use Schumpeterian competition, modelling new GPTs as replacing the old one and never allowing for more than one GPT being used at the same time. Others allow for more than one GPT affecting the application sectors at the same time (van Zon, Fortune and Kronenberg 2003; Schiess 2011).

Aghion and Howitt (e.g. 1998) are able to replicate the s-shaped curve of diffusion, at the same time being able to explain the productivity paradox taking into account time lags and critical masses of users of a GPT needed to unfold a GPT’s full effect (Schiess 2011). However, these models are ignoring the importance of networks and different network settings within and between the application sectors, the effect a GPT has on the industry architecture of a sector, and possible backward, forward and spill-over effects.

Carlaw and Lipsey (2006) provide a central model focussing on the invention of GPTs and the importance of R&D efforts. The authors model three sectors (fundamental research, applied research, consumer goods), each of which has its specific production function. Continuous growth in the model is only possible through the repeated introduction of a new GPT. Uncertainty exists concerning the effects of R&D activities on the sequence of GPT arrivals and effect they unfold. However, the model also has some shortcomings: it keeps the emergence of GPTs exogenous, it does not model the different effects of the GPT on different sectors and it does not model the emergence and diffusion of the new GPT knowledge within the system. With a network approach in which innovations emerge from the collaboration of actors by combining their knowledge, GPT emergence could be endogenised.

5.4.2.2 Nanotechnology as general purpose technology

With the literature on GPTs outlined, the question arises which technologies are GPTs. Undisputed examples for GPTs can be found in computers (Helpman and Trajtenberg 1994) and the steam engine (Lipsey, Carlaw, and Bekar 2005). More disputed examples include laser technology or biotechnology (Lipsey, Bekar, and Carlaw 1998). Several studies have attempted to identify nanotechnology as a GPT, of which two should be named here explicitly:
Based on the definition of Bresnahan and Trajtenberg (1995) for which a technology to be a GPT has to shows pervasiveness, inherent potential for technical improvements and innovational complementaries, Youtie, Iacopetta and Graham (2007) conduct an analysis of patents and patent citations, concluding that nanotechnology show these characteristics and may therefore considered to be a GPT. Teichert (2012) also draws from this definition of GPTs and analyses patents and publications on the level of growth rates, diffusion and citations, also underlining that there is strong evidence for nanotechnology to be a GPT.

The strong evidence given in the literature on the GPT character of nanotechnology therefore can justify the use of nanotechnology data to validate and later calibrate a GPT version of the SKIN model.

5.4.2.3 The uniqueness of general purpose technologies

A separate simulation effort for GPTs requires this type of technologies to have decisive different features from other, ‘standard’ technologies. GPTs are technologies which are used in a much broader range of sectors than other technologies, they are evolving themselves by innovation and at the same time requiring many other complementary innovations, stemming from multiple other sectors. It is the combination of these three characteristics (pervasiveness, inherent potential and innovational complementaries) which make GPTs a proper field of research.

From a knowledge perspective, it seems also reasonable to treat GPTs differently from other technologies. Due to its interdisciplinarity (Porter and Youtie 2009) nanotechnology as a GPT merges formerly unconnected or only weakly connected disciplines. In this respect aspects of cognitive proximity, cross-fertilisation and knowledge complementarity are playing an important role seen from a GPT perspective (Teichert 2012). The combination of before un-combined technologies in turn may lead to the broad applicability (Nikulainen 2010) or generality of nanotechnology, which can for instance be applied in different sectors such as biotechnology and ICT. According to Bresnahan and Trajtenberg, (1995) the application is characterised by two different types of externalities. Within the AS, nanotechnology knowledge might trigger innovations (e.g. nano-based pharmaceuticals) by combining the nanotechnology knowledge with the knowledge of the AS, defined as a vertical externality based on complementariness (e.g. nano-enabled bio-sensors). Between the ASs, the GPT can have horizontal externalities following from its generality where knowledge of these formerly unconnected fields is combined using the GPT knowledge. These trajectories of emerging GPT knowledge and the merging effect it may have should be reflected in the structure of the knowledge network in the SKIN model.
As for the collaboration between firms, GPT innovation networks can be expected to show similar characteristics to the networks of knowledge, which is creating new cross-sectoral connections not only directly between the ASs (in step 3 and 4 in the value chain depicted in Figure 23) but also through firms and sub-networks specialised on the GPT knowledge (step 1 and 2, Figure 26). Thus GPT networks, i.e. networks of firms specialised in the GPT, may not only have their own characteristics and evolutionary trajectories, they also connect networks with different structures increasingly down the value chain where nano-enabled products are applied, thereby influencing their evolution and getting influenced by them.

![Figure 26: The nanotechnology value chain](image)

As for the knowledge perspective, from the innovation and collaboration perspective it again seems to be reasonable to treat GPT in innovation networks differently than other innovation networks.

Policy measures for GPTs should also differ from 'standard' policy measures for several reasons. As Genet et al. (2012) have found technology transfer patterns in the nano sector are closer to that in microelectronics than to biotechnology. Also, the knowledge transfer between large firms and research institutes seems to play a bigger role in nano-electronics than in nano-biotechnology. Therefore they argue, the implementation of policy measures from biotech in nanotechnology would be inappropriate (Genet et al. 2012). It seems reasonable to argue that nanotechnology policy measures should take into account the characteristics of nanotechnology research and innovation in general and the application sector specific R&D patterns in particular. Another example can be found in the discussion about nanotechnology safety, which plays a decisive role in nano-medicine and nano-food, but is almost non-existent in nano-electronics.
5.4.3 Modelling GPT networks from a knowledge perspective: Identifying GPTs in SKIN

5.4.3.1 Stylised facts of nanotechnology as a GPT

In the following, several stylised facts mainly drawn from the literature review and the definition of GPTs are described and applied to the standard SKIN model. This will show whether and to what extent the existing basic SKIN model is already capable to replicate these stylised facts as well as some results from the Irish case study.

Investigating the knowledge level of the SKIN model, we look at two of the most important characteristics of GPTs and draw some hypotheses how these characteristics should be reflected on the knowledge level in the SKIN model. The indicators proposed investigate how knowledge evolves, spreads throughout the network and how the different pieces of knowledge are related to each other. As Hall and Trajtenberg (2004) state, to identify GPTs and confine them from non-GPTs, it is necessary to take a multivariate approach since looking only at one indicator ‘may be misleading’ (p. 7). Again, we are basing the identification of indicators on the definition of GTPs given by Bresnahan and Trajtenberg (1995) who define GPTs as pervasive, having inherent potential for technical improvements and go hand in hand with the development of innovational complementaries.

The first two indicators are mainly drawn from Teichert (2012) and adapted for application to the SKIN model. For all SKIN runs, we use the same input values for most parameters, which are:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Firms</td>
<td>200</td>
</tr>
<tr>
<td>Number of Products</td>
<td>50</td>
</tr>
<tr>
<td>Number of inputs</td>
<td>4</td>
</tr>
<tr>
<td>In-out-products</td>
<td>10</td>
</tr>
<tr>
<td>Initial capital</td>
<td>16000</td>
</tr>
<tr>
<td>Attractiveness threshold</td>
<td>0.3</td>
</tr>
<tr>
<td>Success-threshold</td>
<td>1000</td>
</tr>
<tr>
<td>Reward-to-trigger start-up</td>
<td>1200</td>
</tr>
</tbody>
</table>

Table 5: standard scenario parameter settings

We only vary the share of big firms (1% and 5%) and the partnership strategy (conservative and progressive) as these parameters have turned out to have a significant influence on the indicators investigated. The knowledge as represented as capabilities is analysed either when the simulation seems to have ‘initialised’ (approx. 100 ticks) or ‘settled’ (approx. 220 ticks), and where appropriate as well after 160 ticks. The object of analysis are the capabilities in the model and their combination into innovation...
hypotheses (IHs). Furthermore, we divide the available knowledge space of 1000 capabilities into 10 classes of 100 possible capabilities each.

5.4.3.2 Pervasiveness and capability distribution
To be seen as pervasive a GPT has to show a wide range of applications in various other technologies (Teichert 2012). Diffusion is one possible indicator of pervasiveness, measuring the share of innovation hypotheses carrying at least one capability of a certain class. Here, the shares of the different classes have to be compared with other technologies in order to identify whether there is a class applied significantly more often than all other classes. Based on the idea of the GPT having to be combined with knowledge available in the application sector, we would assume that the GPT knowledge is not only highly present in absolute numbers but also used in the majority of IHs, or at least used by an order of magnitude more often than application technology knowledge.

Fig. 27 shows the absolute appearance and diffusion of each capability class over all IHs after 100 ticks over 5 runs (strategy: conservative; 1% big firms). None of the classes seems to be an outlier, since the values appear to be equally distributed. Exemplary, fig. 28 shows the absolute appearance of capabilities after 220 ticks for a progressive strategy. The absolute number capabilities used is smaller however, the pattern of a rather equal distribution is similar. Conducting the same test after 100 and 160 ticks as well as for high (5%) and low (1%) shares of big companies does not change this pattern.
We can therefore claim that none of the technologies is significantly utilized more or less often than any of the other technologies. As described above however, we claim that this has to be the case for a pervasive technology. The pervasiveness of a technology not only manifests itself in the diffusion rate. Empirically, with a GPT being applicable in very different industries, this should be reflected in the patents of this technology. Various authors proposed to measure this wide applicability with a generality index (Bresnahan and Trajtenberg, 1995; Hall and Trajtenberg, 2004; Moser and Nicholas, 2004), based on the citations a patent receives from other but the own technology class. Since this measure suffers from not being a weighted measure, thus assuming all technologies being equally distant from each other (Hall and Trajtenberg 2004), we apply a weighted measure of generality exemplary for one run of the SKIN model with a standard setting after 100 ticks. This technological coherence describes the extend to which the capabilities used in the IHs are similar (see Teichert, 2012). The more similar they are, the more specialised a technology class is.

In the following, an adapted version of the technological coherence approach as proposed by Teichert (2012) is used. First, we calculate the co-occurrence $C_{i,j}$ of capabilities $C_i$ and $C_j$ in all innovation hypotheses in the simulation run according to Antonelli et al. (2010). The resulting matrix gives for each capability how often the respective capability is used together with any other capability in the IHs, with $C_i = \sum_j C_{i,j}$.

We define $N_j$ as the total number of IHs using a capability $j$, with $T = \sum_j N_j$, i.e. the total number of uses of capabilities. This gives the expected number of co-occurrences for each pair of capabilities.
\[ E_{ij} = C_i \frac{N_j}{T} \]

To determine the matrix of technological relatedness, \( TR_{ij} \) between each pair of capabilities we calculate:

\[ TR_{ij} = \frac{C_{ij} + C_{ji}}{E_{ij} + E_{ji}} \]

The technological relatedness values \( (TR_{ij}) \) between each pair of capabilities \( C_i \) and \( C_j \) are then weighted by the relative share of IHs in the respective technologies:

\[ TC_i = \frac{\sum_{i \neq j} C_{i} \times IH_j}{\sum_i IH_j} \]

with \( IH_j \) as the number of IHs using a capability \( j \). Grouping the capabilities available in the simulation into 10 classes, the \( TC_i \) values are added up weighing them by the relative share of IHs using the respective capability. This gives the technological coherence of each class.

Lower values signify that the capabilities in the respective class are used less often with the same capabilities from other classes in the IHs, thus they are combined with a less coherent set of other capabilities. A GPT would thus have a lower \( TC_i \) than a non-GPT. The absolute level of \( TC_i \) is therefore less important than the relation to other technologies. As shown in Figure 29, the accumulated weighted technical coherence of the assumed 10 technology classes only differ very little (mean \( \mu=0.0303 \); standard deviation \( \sigma=8.09E^{-4} \)).

Fig. 29: Technological coherence of capabilities in IHs
Again, the SKIN generates values which appear to be equally distributed, i.e. none of the technology classes is combined with a broader or narrower set of classes than all other classes. We can conclude that none of the classes has a higher compatibility or generality than the others. The criterion of pervasiveness measured by diffusion and technological coherence is therefore not fulfilled yet in the SKIN model.

5.4.3.3 Merging of knowledge and network structures
Analysing the SKIN model and the structure of knowledge networks it reproduces, we focus on the basic structure of knowledge implicitly described above, namely the separation of knowledge in different AS and one or more GPT sectors. It is widely accepted that various networks of knowledge (e.g. patent co-classification networks, citation networks) show some clustering of knowledge for instance in biotech (Cooke 2002) and ICT (Antonelli et al. 2010). Within these clusters or sub-networks, knowledge should be tightly connected, as the bits of knowledge are very similar to each other and combined frequently. Between the clusters however, connections are expected to be relatively sparse. This can also be seen in the empirical data on the co-classification data from Ireland, where the knowledge of most areas clearly clusters.

One way to measure the degree to which a network is separated into densely connected sub-networks was shown by Blondel, et al. (2008) who define modularity as the share of links inside the community relative to all links in the network, resulting in a scalar value between -1 and 1, with highly clustered networks having a modularity closer to 1. With densely connected application sector knowledge and only sparse connections between the AS clusters, we would expect the modularity to be close to 1.

If the knowledge in the networks is merging, for example through the appearance of a GPT, we would expect more connections between the sub-networks to become established, thus the modularity to decrease. This for sure only holds given the connections within the sub-networks do not increase at the same rate. We apply this measure to the capability network in SKIN as shown below, trying to investigate whether knowledge mergence can already be simulated in the basic SKIN model.

The knowledge network in SKIN is based on the utilisation of capabilities in IHs (Figure 30). Whenever two or more capabilities are used in the same IH (*italics*), a fully connected network between these capabilities (circles) is established:
Links between capabilities are weighted, thus the weight of the link between them will be increased whenever these capabilities are combined more than once in an IH (capabilities 42 and 7 are used in IH 1 and 2, capabilities 7 and 13 in IH 2 and 3). From this, we can draw the network of capabilities for the simulation runs in SKIN as seen exemplary in Figure 31. The graph shows the giant component of the capabilities network (616 nodes, 7587 links) with conservative partnership strategy and a low share of big firms (1%). The modularity of this network is 0.53, node and link colours correspond to the sub-network identified by the modularity algorithm.

Fig. 32 shows a network of low modularity (progressive strategy, high number of big firms, 220 ticks) with 298 nodes and 8958 links. It is clearly visibly that sub-networks (application sectors) are hard to detect.

Fig. 31: Example network of capabilities – high modularity
Figures in Table 6 show the modularity coefficient for various settings and are averaged over 5 runs per scenario. The empirical data based on co-classifications of patents with an Irish assignee gives us a modularity of 0.71, supporting our hypothesis of a network of different pieces of knowledge, clustered in sub-networks with sparse connections.

The simulated data clearly shows the influence of the partnering strategy on the evolution of modularity. In the progressive scenarios, modularity tends to decrease faster, i.e. the knowledge merges at a higher rate. In the progressive setting companies tend to chose partners with more distant knowledge, thus connections to other sectors are established more quickly than in the conservative scenario, where companies tend to chose similar partners. Also, the influence of the share of big firms is clearly visible. This might stem from big firms having a larger set of capabilities, thus leading to a higher probability that capabilities get combined when they are in the same firm than when they are distributed across firms.

<table>
<thead>
<tr>
<th></th>
<th>Big firms 1%</th>
<th>Big firms 5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Empirical case</td>
<td>0.71</td>
<td></td>
</tr>
<tr>
<td>Conservative</td>
<td>0.524/0.534/0.479</td>
<td>0.589/0.498/0.288</td>
</tr>
<tr>
<td>(100/160/220)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Progressive</td>
<td>0.181/0.197/0.184</td>
<td>0.23/0.174/0.155</td>
</tr>
<tr>
<td>(100/160/220)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6: modularity of capability networks

The simulated values seem to support that knowledge merging is already emerging in the simulation. However, in the previous section the existence of GPTs in the SKIN model could not be supported. Since all characteristics of a GPT have to be fulfilled in
order for a technology the be such, the knowledge merging taking place cannot be traced back to the influence of GPT capabilities, but only to the factors already mentioned (partnering strategy and share of big firms). Additionally, the extend to which the knowledge merges, resulting in a network of capabilities of uniform connectedness, does not seem to be supported by the empirical case.

5.4.4 Further work – indicators and SKIN adaptation

Indicators

As we could show with the indicators and network structure and model behaviour above, GPTs are clearly not yet emerging in the SKIN model. Changing the SKIN model in a way that it shows the behaviour described seems possible. However, further stylised facts from the literature were not yet taken into account, since they are mainly based on indicators not to be implemented straight forwardly:

- GPTs show scope for on-going technological improvement: According to Teichert (2012), with accelerating growth rates of GPT-inventions (Palmberg and Nikulainen 2006) and forward citation rates in patents (Hall and Trajtenberg 2004) as well as in publications, at least two measures can be found in the literature.

  In the SKIN model, numbers and growth rates for IHs using at least one ‘GPT’ capability could be computed as a measure of inventions using the emerging GPT. Forward citation rates could be based on the inputs an IHs uses and the capabilities required in order to manufacture these inputs. The equally distributed use of all technologies even after a high number of ticks indicates however that none of the technology classes outperforms any other class over a longer period of time.

- GPTs spur innovation in application sectors: the major indicator for a GPT such as nanotechnology to spur innovations in other sectors along the value chain is the diffusion rate of the GPT knowledge (Shea et al. 2011) as well as the growth of classes citing the GPT (Hall and Trajtenberg 2004). A measure for diffusion has already been described in Chapter 5.2. The second indicator may be compiled by identifying the growth rates in terms of IHs assigned to the classes citing or using GPT knowledge. Since this knowledge enables new innovations in the classes it is combined with, a higher growth rate of these classes as compared to other AS classes which are not (yet) combined (Teichert 2012) is to be expected.
As stated above, one stream of GPT literature identifies the development of complementaries to be combined with the GPT as one major prerequisite for the GPT to unfold its economic potential. Bresnahan and Trajtenberg (1995) already introduced the concept of vertical and horizontal externalities, horizontally between different AS and vertically between the GPT sector and the various AS. The complementariness can again be computed with the help of citations relating the number of second generation citations of the GPT to all other citations not towards the GPT. In the SKIN model, input chains over two steps would have to be calculated in order to measure the complementarity index.

**Knowledge and value chain implementation**

In order to simulate the GPT character of nanotechnology in a more sophisticated way as currently done in SKIN, the application of genetic algorithms (Birchenhall, Kastrinos and Metcalfe, 1997) seems to be a promising alternative. Products would require a combination of at least two strings of knowledge, one from the application technology and another from the GPT. Mutations of the genes could provide a source of entirely new knowledge in addition to radical research. Internal and external selection mechanisms (Geisendorf 2010) would provide a two step selection process, ensuring both, technological feasibility and marketability.

On the product level in SKIN, value chains with producers of raw materials, intermediates and end products already exist. However, a specific GPT sector running parallel to the value chain and having links to all other steps of the value chain as described in Section 5.4.2.3 is not yet implemented. This is especially important since this may have different effects in the simulation such as a direct dissemination of knowledge from the raw materials sector to the end products sector or additional sources of innovation by connecting the lateral link to the other chain links. A differentiation between GPT actors and application actors in the model would replicate the value chain more realistically and allow for different characteristics of the actors: there is evidence for example that the nano-tools sector is dominated by SMEs and start-ups, whereas in the application sector MNEs dominate the market (Gómez-Uranga et al. 2011).

**5.4.5 Conclusions**

Nanotechnology is showing strong signs of being a GPT emerging thus generating huge interest of policy makers wanting to effectively influence nanotechnology evolution. Since there is strong evidence in the literature about nanotechnology being a GPT, the uniqueness of GPTs as compared to other 'standard' technologies, makes a separate modelling attempt for nanotechnology as a GPT reasonable. A set of indicators to identify
GPTs was developed, based on their definition. Two of the main characteristics (pervasiveness and the knowledge merging effect) were applied to the standard SKIN model. Neither the diffusion of capabilities nor their (in)coherent use in within the model allowed for an identification of GPT knowledge in SKIN. Analysing the capability networks of SKIN not only showed excessive signs of knowledge mergence, but this also did not result from the existence of GPTs.

Besides the indicators applied, three more stylised facts from the definition of GPTs and the respective measures are introduced. Since they all are based on citations, a meaningful representation within the SKIN model has to be identified or constructed. For the purpose of modelling two distinct types of knowledge with different characteristics, the introduction of a more sophisticated knowledge representation, combination and selection is proposed with the genetic algorithms. Finally, improvements for the value chain are proposed.

The SKIN model may not yet be a meaningful simulation when it comes to general purpose technologies such as nanotechnology. It provides however a useful starting ground for the simulation of GPTs from a knowledge-based perspective for which we have introduced the indicators necessary to identify GPTs in SKIN.
5.4.6 References


Helpman, E. and Trajtenberg, M., 1994. A time to sow and a time to reap: Growth based on general purpose technologies.


6 Discussion of Findings

Below, the main research results of the publications included in this thesis are summarized, as well as conclusions regarding the research questions and the overall research project are given. Subsequently, implications based on the findings are outlined. Next, the main limitations of the results are stated. The chapter concludes with illustrating some possible paths for further research.

6.1 Summary and Conclusion

Research for this doctoral thesis was motivated by the realisation that nanotechnology became increasingly important for policy makers, for example in Ireland (cf. Forfás 2010). In this thesis, as opposed to other ‘standard’ (i.e. non-GPT) technologies, GPTs can have a much broader impact on the economy. On the one hand, this makes them attractive to policy intervention, on the other hand, this policy intervention should allow for a higher degree of complexity when designing policies targeting GPTs.

In this thesis, I explored some research questions related to GPTs in a computational social science approach taking a knowledge perspective. Researchers of computational social sciences specialising in policy modelling give advice to policy makers based on computer simulation models and empirical findings. If a simulation approach is to be taken for a GPT, such as nanotechnology, what are the properties of such a technology?

The main questions of the empirical study were:

- Are GPTs different from other technologies from a knowledge perspective?
- Are these differences revealed by analysing a network of knowledge?

The aim of this publication has been to analyse the knowledge of the Irish innovation system and how nanotechnology as the most recent and promising example of an emerging GPT is interwoven with other patents in the Irish national innovation system. Policy implications would be different if nanotechnology could be applied to many areas showing no or only weak interdependencies between those technologies, or in cases where nanotechnology is not only applied to many areas, but also connects those areas.

All patents with Irish assignees were analysed applying a social network analysis approach. Research outlined in Chapter 5.1. reveals that nanotechnology is widely distributed among patents, thereby connecting otherwise loosely connected technology fields. This implies that applications of nanotechnology in one technological field may have strong feedback effects on other areas as well. Additionally, the structure of the network and network statistics generated could be used for validation of simulation results in Chapter 5.4. Findings of the empirical study are important, since on the one hand, they provide a data basis for validation of the simulation results of a possible simulation of GPT-innovation networks. On the other hand, the results entail further
implications for possible policy interventions aiming at GPTs. Results indicate that there is no one-size-fits-all policy making for nanotechnology since it is prone to many interdependencies and connections, even more so than any other "standard" technology. It was therefore important to find out whether nanotechnology can be applied in many areas showing no interdependencies between those technologies, or whether nanotechnology is not only applied in many areas, but also connects those areas. It was found that at the current stage, nanotechnology is rather a loosely connected field. Connectivity between the different field seems to be increasing – nanotechnology is getting more multidisciplinary. Revealing this interconnectedness was important as conclusions could be drawn from this for policy making.

Most policy measures aim at the support of R&I to order to foster economic growth via innovation activities. However, alternative policy goals are given more attention. If a computational social sciences approach to GPTs aims at the development of a future-proof concept of policy modelling, its framework needs to be capable of integrating these alternative policy goals. The next research question is therefore aimed at the future value of modelling policies if answering this type of questions becomes increasingly important:

- Can the descriptive Systems of Innovation framework be used to integrate normative questions which arise from the emergence of nanotechnology?

In Chapter 5.2 the normative approaches of RRI and inclusive research were outlined and it was shown how they can be combined with the descriptive framework of the systems of innovation approach. Normative policy questions can be linked to the systems of innovation approach and thus be analysed and validated based on the methods of computational social sciences. This has led to the conclusion that policy scenarios for normative policy making can be developed. The effects of such policy measures can be traced e.g. on the level of networks and thus the simulation of normative policy scenarios and the validation of the results is possible.

In order to assess knowledge, how it emerges, evolves, and disseminates through a system, it needs to be appropriately modelled. If a way to model knowledge in a computer based simulation is found, that simulation also needs to be suitable for the development of research policy scenarios:

- How can knowledge represented in an ABM in order to develop and evaluate policy questions?

In Chapter 5.3, a representation of knowledge in bit strings was developed and tested for its policy simulation purpose. The model developed shows feedback effects: products of films are accepted to a certain degree by the consumers; the degree of acceptance leads to reaction of firms. With non-linear effects, such as market saturation and emergent phenomena such as variable firm size distributions, some of the most
important aspects of complexity can be found in the model. This has therefore led to the conclusion that even a simplistic ABM is already suitable for representing complex social systems. Based on this model, it was also possible to draw policy implications and develop policy scenarios. It can be concluded that also the methodology of ABM, too, is well suited for the research goal.

Due to the lack of emergence of relations between the bit streams and interaction between firms, an existing ABM platform, the SKIN model, is identified and applied in the subsequent chapter(s). With the SKIN model, an already quite powerful agent-based simulation platform for policy modelling is at hand, and it is investigated, whether it suitable for the purposes of the research project:

- Can GPTs already be identified in the SKIN model, and if so, how?

Based on GPT literature, a set of indicators was developed to determine whether in SKIN GPTs, represented as capabilities, can already be identified. Applying the indicators revealed that GPTs cannot be identified yet in the existing SKIN model. Hence, further steps for an adaptation of the SKIN model regarding the integration of a larger set of indicators and changes to the model core were outlined, to design a sound representation of GPTs in a knowledge-based model of innovation networks. The assessment of the SKIN model thus revealed that GPTs do not emerge from a knowledge base in which all knowledge equally structured in a sense that there are no differences in the simplicity of applicability, in its effects on the quality of the products in which the knowledge is used, or in its effects on the productivity in the production process.

The aim of this dissertation was to lay the foundations for a computational social sciences approach to policy modelling focussing on GPTs. The steps taken were necessary to determine the relevance and appropriability of the proposed framework. It was shown that a distinct approach to GPTs in policy modelling is justified. GPTs (here nanotechnology) reveal a high degree of interconnectedness with many other technologies. This additional degree of complexity poses a certain challenge for policy makers since it makes the design of effective and efficient policies for fostering GPTs even harder. With a complex social sciences perspective framed by the SI approach, it is possible to also integrate normative policy goals, which are of increasing importance. In that sense, the approach outlined can be regarded as ‘future-proof’.

With agent-based modelling, it is not only possible to represent knowledge in such a way, that complex characteristics of knowledge can be captured. ABMs are also well suited to drawing policy implications from simulation results and to simulating alternative policy scenarios. With the existing SKIN model, which has already been applied numerous times to policy modelling (Ahrweiler et al. 2016), a solid basic model already
exists. However, based on the GPT indicators developed from theory, it could, however, be determined that the basic SKIN model is not yet fit for simulating GPTs in innovation networks. With the changes outlined and the first simulation results with the adapted and reduced SKIN model, the integration of GPTs in the model already looks promising.

6.2 Limitations and implications

Empirical data

The empirical study presented is limited by the quality of data available and the differences in patenting behaviour in technology sectors. Data availability is limited in the sense that it would have been possible to shed more light on the nanotechnology innovation system in Ireland if fine-grained firm data had been available. Data like this exists e.g. at the Central Statistics Office. For the purposes of analysing the network however, firm-level data would have been necessary. Despite several attempts, it was not possible to obtain such data due to data protection regulations. The main reason for this is the overall comparatively small size of the innovation system. Hence, the small number of actors would have made it impossible to reliably anonymize the data. Nevertheless, it was possible to shed light on the knowledge available and its structure using patent data. The limitations of patent data are obvious and well-known in research. It is, however, very often the best data that is available.

Further limitations regarding the agent-based model applied can be found in its missing calibration with real world data. The model presented in in Chapter 5.3, however, places the focus on discovering and explaining emergent phenomena (e.g. the distribution of firm sizes), heterogeneity of agents and knowledge, as well as feedback effects (e.g. the reaction of firms to changed consumer demand). As such, a calibration with empirical data would be appropriate at a later stage of development of the model. As stated below, the limitations of the agent-based model are appropriately considered in the interpretation of results.

Adapting existing models

Adapting an existing and accepted model such as the SKIN model carries the advantage of using a well-tested and valid basis. However, there is also a downside to this approach: An existing model may also capture aspects which are not central to the research question. They may detract the attention of the researcher from the actual research question and show effects which are of little to no importance concerning the research in focus. For this thesis, however, the SKIN model provided a comprehensive and powerful simulation environment. Effects which were of no decisive interest to the research conducted could easily be ignored.
The implications of using ABM in policy advice are mainly methodological: Since ABM is a powerful tool for research, it comes along with the possible fallacy of being overestimated. On the one hand, the research showed that even with a simplistic model, complex behaviour can be modelled. On the other hand, it has also revealed that such models can easily become overly complex. This analysis and interpretation of results therefore requires accuracy and attention if false conclusions or over-interpretations are to be avoided.

Policy implications and contributions

The research presented in this thesis entails numerous implications for, first and foremost, policy makers in innovation policy as well as for researchers. Below, several of these implications are outlined for all publications and the thesis as such.

The emergence of a GPT may affect and fundamentally change several sectors and thus the entire economy within a relatively short time span. Policy makers need to be aware of the specific characteristics of GPTs in terms of their applicability, wide use and innovation spawning effects. Policies aiming at fostering GPTs should take these properties into account to be effective and efficient. These measures should be different from policy measures for other ‘standard’ technologies. In the following, some of these differences and important aspects to be considered will be outlined.

As stated above, due to their broad effects on the economy, GPTs are a very attractive subject for policy makers. However, these multiple effects also lead to great responsibility in policy making. Ill-designed policies for GPTs may have consequences for more than the sector targeted. A loss of competitiveness of multiple sectors may be the consequence if GPTs prone to application in these sectors are either unavailable or lacking quality. For instance, if policies fail to foster the developments of appropriate nanotechnologies, this might have consequences for the competitiveness of downstream sectors such as ICT or the automobile industry using ICT technology. Policy makers dealing with GPTs must be aware of these multiplicative effects when designing R&I policies for GPTs.

These multiplicative effects may also cause market failures – in terms of underinvestment in R&D, as described in Chapter 2.2 to be even more harmful with respect to GPTs. While these effects on the one hand make investments in GPT R&D even more attractive, possible underinvestment due to uncertainties or inappropriate institutions entail even higher opportunity costs due to lack of investments and innovations not realised. Underinvestment in GPTs affects more sectors than underinvestment in application technologies and thus has more severe consequences for innovation and growth.
The emergence of GPTs, however, also bears consequences for qualitative growth. Fundamental structural changes in the innovation system may arise from the emergence of a GPT, with new types of collaborations crossing sectoral and technological boundaries. GPTs may cause disruptive changes for one or more sectors within a relatively short time span (as for example ICT). R&I policies may account for that by supporting adaptation processes needed in those industries affected. Furthermore, the emergence of a GPT may also change interdependencies between sectors. As shown in Chapter 5.1, previously loosely or ‘un-connected’ sectors may become interdependent during the evolution of a GPT, such as nanotechnology. The more multidisciplinary a GPT is, the more developments in one application sector will affect other sectors. A one-size fits all policy approach may thus not seem appropriate for GPT policy making, but rather a targeted approach which reflects the multiple sector effects of a GPT seems the more appropriate the higher the degree of interconnectedness of the GPT. As an example, the current Irish strategy for research and innovation may be evaluated. On the one hand, a concentration on only some application areas of nanotechnology as is currently the practice in Ireland (Research Prioritisation Steering Group 2011) may help to concentrate research funding and eventually result in a deepening exploitation of the respective technologies. Since GPTs can unfold their potential only in combination with application sectors (development of complementaries), policies fostering GPTs should be designed in coordination with policies targeting the respective application sectors, leading to a co-evolution of both, the GPT and the application technology. A concentration of R&I policy on just one of the two may cause the targeted technology to forge ahead and the neglected technology to limp behind. Advances made, for example, in nanotechnology would not find a matching application in biotechnology and thus lead to inefficiencies and sub-optimal investments in both technologies.

This need for complementaries also implies much greater emphasis on policies ensuring an appropriate level of heterogeneity within the knowledge base of an economy. Heterogeneity is one of the main sources of innovations as was outlined in Chapter 2. Regarding GPTs, heterogeneity is also needed to ensure the evolution of both, the GPT and the application technology. In this sense, the concept of GPTs underlines the importance of policy measures to aim for a diverse knowledge base in science and industry. A lack of heterogeneity may not only lead to fewer innovations in a certain sector, it may also lead to fewer innovations which could have resulted from an application of a GPT in another sector. Heterogeneity also poses a challenge: as stated in Chapter 2.2, heterogeneity poses an obstacle to fast and efficient dissemination of innovations, giving rise even to normative
questions as was outlined in Chapter 5.2. Insufficient dissemination regarding GPTs implies even greater consequences than insufficient dissemination regarding a standard technology. If GPTs are not available or accessible to larger parts of the population or economy, these parts may trail in their development or even fall behind when GPTs not only open up new development paths but also render existing technologies (GPTs and application technologies) obsolete. Policy making is put under even greater pressure in the light of GPTs and normative questions about regarding justice become even more prominent.

However, not only the access to GPTs but also the capacity to absorb them and put them into application in innovations must be considered in policy making. While GPTs may enable the combination of previously incompatible technologies, actors must be able to develop the capacity turn these new opportunities into innovations. One can easily imagine that the combination of a living cell and a microprocessor would require the internalisation of some distant knowledge for both parties involved. People having previously dealt with microprocessors would have to at least develop some understanding about living cells at the nano-scale, and biologists would have to be aware of the functionalities of a microprocessor. Thus, with respect to the emergence of GPTs, policies aiming at supporting the development of absorptive capacities gain even more importance.

This may involve policies targeting institutions within the innovation systems, which also need to account for the far-reaching effects of GPTs. Institutions in place for certain sectors may prove inefficient or even harmful for the evolution of GPTs. Policies targeting the collaboration within certain sectors and the intrinsic innovation networks may neglect that there are potentially new connections to other sectors via the possible GPT. One recent example can be found in the challenges the application of ICT poses to the automotive sectors. With ICT, artificial intelligence facilitated the development of autonomous vehicles. Institutions in place such as regulations concerning liabilities in the event of an accident, however, are rendered insufficient for dealing with accidents caused by artificial intelligence.

But not only institutions, pre-existing innovation networks and clusters, too, are affected by the emergence of GPTs. New, previously impossible collaborations between actors of different types may be promising but also pose a challenge to the participating actors. A previously unlikely collaboration between a pharmaceutical company and a research group developing microprocessors may be promising since the capabilities of the research group to manipulate atoms at nano-scale facilitate the development of targeted drug delivery techniques. R&I policy may provide interface agencies enabling and coordinating the collaboration between science and industry and foster the dissemination
of knowledge. These agencies may become even more important with respect to GPTs since GPT knowledge must be transferred across sectoral boundaries.

For policy makers, the concept of GPTs implies many consequences. Policies need to consider the enormous potential of GPTs for creating innovations. GPTs increase the complexity of the system, thus policy making becomes a greater challenge since it needs to reflect this increased level of complexity within the system. Otherwise, policies could become ineffective and inefficient leading to high costs and missed chances for innovation.

**Theoretical implications and contributions**

With the SI approach a powerful framework innovation system analysis is at hand. As shown in Chapter 2.2 even normative concepts might be integrated and policies developed based on the SI approach. In combination with the concept of GPTs the question arises how suitable the SI framework might be utilized for analysing and supporting policy making regarding GPTs. In the following, it will be shown how the three approaches (national, regional, sectoral) and their important aspects are could be suited for GPT policy making.

In the NIS approach, a strong emphasis is on institutions and institutional factors for supporting R&I. In Chapter 5.2 is was shown that normative issues, e.g. about the access to nanotechnology, can be combined with the NSI approach. Furthermore, for developing policies aiming at GPTs, it is for example necessary to consider cross-sectoral effects of GPTs. As outlined above, with GPTs developments in GPT may differently affect the evolution in various application sectors. Therefore, a coordinated policy approach considering these effects is necessary to design efficient policies. Furthermore, policy coordination is needed to ensure a sufficient level of heterogeneity within the knowledge base of actors. For sure not all, but many institutions should be in place on a national, or maybe even supranational level.

The RIS approach emphasizes the importance of localized knowledge sharing through collaboration at the regional level for example within clusters or regional collaboration networks. Also, institutions supporting this collaboration are given great attention. Due to the relatively high knowledge distance between (see above example), local proximity may be even more important when GPTs are involved. At local level, especially tacit knowledge is more easily shared supporting the innovation processes. Thus, also institutions at a local level would be even more important.

At the core of SIS are the characteristics of certain technologies leading to the emergence of sectors. The approach also seems well-suited for application to GPTs. Boundaries of the system are defined by the technology. On the one hand, this may prove difficult since the debate on nanotechnology (e.g. where exactly is the border
between micro-technology and nanotechnology?) showed that it is sometimes hard to tell where these boundaries are. This is even more the case for fast evolving technologies at their early stages of development. In this phase, the limits of the filed are often yet to be defined and sometimes change greatly due to unexpected developments within the field, whereas at later stages of a technology, incremental changes are more prominent.

On the other hand, this approach seems to be helpful exactly for the reason of defining the limits of the system intrinsically. As shown above, nanotechnology for example shows a wide range of applicability and thus effects many sectors. If the limits of the sector change permanently, the system in consideration would change with them. It is, however necessary not to concentrate the analysis of one application sector for example since the interdependencies with other sectors increase with the applicability of a GPT. Furthermore, also in the SSI approach institutions are very important, especially sector specific institutions. Specific institutions for one sector may on the one hand be supportive for technological development and innovations in the respective sector. On the other hand, institutional set-ups must not be too specific or at least not to static. With the application of a GPT existing institutions may be challenged since entirely different combinations as before become feasible.

This work contributes to the theory of GPTs by showing that GPTs do not emerge in standard models of knowledge representation. Hence, GPT knowledge may be regarded as a special type of knowledge, underlining the usefulness of the concept. This usefulness is further supported by outlining GPT-specific innovation policy approaches. Theory on policy making may also profit from the this work in since it strongly suggest that policies targeted at GPTs should not be the same as policies targeting standard technologies, but these policies need to take into account the characteristics and complexity increasing effects of such broadly applicable technologies, such as nanotechnology.

To the framework of innovation systems this work contributes by showing that the combination of the SI approach with the concepts of RRI and inclusive innovation is not only possible but also entails some broader implications: on the one hand, combining normative questions with the descriptive framework of the SI approach may look promising. Researchers of the SI approach may be able to develop effective policy measures in order to pursue a normative goal set. On the other hand, the SI framework might be weakened by these normative goals. If these goals introduce societal or political prescriptions, the SI approach might loose its (aspired) neutrality.
6.3 Further research

Further research based on the work presented in Publication 1 could be focussed on applying improved methods such as analysing the network structures by using dynamic network analysis. Dynamic analysis would help to reveal the effects of changes on the classification system or certain policy measures on the development of the network structure. Analysing the network structures in more detail in order to reveal the connections between patent classes, patents, and patent holders would help to understand the roles different actors play in certain technology classes and which of these actors might help transferring and applying certain nanotechnology developments from one application area to another. Additionally, the same methods could be applied to the patent networks in other countries in order to reveal national differences.

Regarding Publication 2, one path of research could be to develop specific policy questions based on RRI and inclusive innovation, and the aims they imply. A set of scenarios and expected effects on innovation at the level of agents, knowledge (e.g. knowledge diversity), and networks would be the next promising step. Implementing those measures in a policy modelling and simulation platform would be the next subsequent step in order to evaluate the policy measures ‘ex-ante’.

The model of knowledge representation in bit strings as outlined in Publication 3 could be extended by introducing collaboration and knowledge exchange between agents. Furthermore, the model does not yet entail networks between different knowledge bits based on their combination in products. The approach, however, is promising for it opens up the possibility to incorporate the distance between pieces of knowledge. This could, for example, be realised by interpreting the position of bits within the bit strings. Modelling knowledge distance in this way would allow for the implementation of parameters representing the ease of combination of two or more bit strings. Possible research paths with this approach could be models of absorptive capacity or knowledge landscape models.

Based on Publication 4, and 5, a SKIN model could be developed with which an assessment of the diffusion of GPTs within the system would be possible. Another major step forward would be to have GPTs in the model emerge from the recombination of knowledge, knowledge exchange, and knowledge creation. Based on this, a wave-like occurrence of new GPTs in the system could make this knowledge-based model an alternative to the current, mostly neo-classical approach to GPTs.

Overall, this thesis provides the foundation for many different research paths. In order to support policy makers in designing an appropriate research and innovation policy framework for GPTs and as such nanotechnology, further work on the model as proposed is needed.
7 References


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Appendix

Netlogo code for chapter 5.3

; This model is about representing knowledge. Inspired by the wide field of genetic algorithms (GA) the main idea is to represent knowledge as Bit-Streams.
; main questions to deal with: how does demand effect the evolution of knowledge
; and how can the evolution of general purpose technologies be modelled with GA
;
; Matthias Mueller (University of Hohenheim) and Benjamin Schrempf (University College Dublin)
;
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;
extensions [profiler]
breed [Firms Firm]
Breed [Consumers consumer]
breed [knowledge-bits knowledge-bit]
undirected-link-breed [ihs ih]
directed-link-breed [innos inno]

; Firms are defined, at this stage with just three knowledge units, open to discussion (eg. small and large firms)

Firms-own
[
    c1
    c2
    c3
    knowledge-list
    mapped-knowledge
    selling?
    product-ID
    sales
    strategy
    buyers
    list-of-sales
    age
    last-innovation
    resource
]

; consumers are defined

consumers-own
[
    needs
    sellers
    last-seller
]

Globals
[}
mapping-function; variables for the mapping functions of all product characteristics
product-id-mapping-function; the MF which decides the product category for each firm
average-fitness; the average fitness in the simulation
global-needs; list of all available needs
list-of-knowledge
average-fitness-product-0
number-radials-product-1
number-incrementals-product-1
]

; knowledge bits are spread over the netlogo grid
knowledge-bits-own
[
  a-coord
  b-coord
  name
]
innos-own
[
  link-age
]

To Setup
cacreset-ticks
ask patches [set pcolor white]
create-product-id-mapping-function
create-mapping-function
create-firms N-firms
[
  set shape "factory"
  setxy random-xcor random-ycor
  set color green
  get-knowledge
  map-knowledge
  set selling? false
  set sales 0
  set list-of-sales []
  set age 0
  set resource 20
]
create-global-needs
create-consumers n-consumers
[
  set shape "house"
  set color red
  setxy random-xcor random-ycor
determine-needs
  set last-seller firm 0
]

if show-knowledge
[  
  ask firms [set hidden? true]; firms are not visible  
  ask consumers [set hidden? true]; consumers are not visible  
  set list-of-knowledge []; creates a list of the length of the number of knowledge bits  
]

let counter 1  
repeat 2^possible-knowledge-space-2^n  
[  
  set list-of-knowledge lput counter list-of-knowledge  
  set counter counter + 1  
]

set list-of-knowledge map [bit-sequence?] list-of-knowledge; maps all bit sequences e.g. bit sequence 1 is 0101001001 it would put it to the list

let splitted-list-a-coord [sublist ? 0 (possible-knowledge-space-2^n / 2)] list-of-knowledge; maps circles on the grid representing the knowledge bits available

set splitted-list-a-coord map [decimal-number?] splitted-list-a-coord  
let splitted-list-b-coord map [sublist ? (possible-knowledge-space-2^n / 2) (possible-knowledge-space-2^n)] list-of-knowledge  
set splitted-list-b-coord map [decimal-number?] splitted-list-b-coord  
set counter 0  
foreach list-of-knowledge  
  [  
    create-knowledge-bits 1  
  ]

if show-innovation  
  [ ]
end

to-report bit-sequence [temp-decimal-number]  
let counter temp-decimal-number  
let temp-bit-sequence []  
while [counter != 0]  
  [  
    ifelse counter mod 2 = 0 [set temp-bit-sequence lput 0 temp-bit-sequence]  
      [set temp-bit-sequence lput 1 temp-bit-sequence]  
    set counter floor (counter / 2)  
  ]
while [length temp-bit-sequence < possible-knowlegde-space-2^n]
    [set temp-bit-sequence lput 0 temp-bit-sequence]
report reverse temp-bit-sequence
end

to-report decimal-number [a]
let b a
let temp-id 0
let counter 0
repeat length b
[  
    if last b = 1 [set temp-id temp-id + 2 ^ counter]
    set b but-last b
    set counter counter + 1
]
report temp-id
end

to create-product-id-mapping-function; creates a random product-id mapping function of
    the structure 1,2,3,1,2,1,2 with the length corresponding to the number of bits
set product-id-mapping-function []
repeat possible-knowlegde-space-2^n
[
    set product-id-mapping-function lput random 3 product-id-mapping-function
]
end

to create-mapping-function; creates for each product and each characteristic a mapping
    function of the structure 1,2,1,2,3,1,2
set mapping-function []
repeat number-of-products
[
    let counter2 []
    repeat number-of-characteristics
    [  
        let counter []
        repeat needs-length
            [  
                set counter lput (sentence random possible-knowlegde-space-2^n random 3 ) counter
            ]
        set counter2 lput counter counter2
    ]
    set mapping-function lput counter2 mapping-function
]
end

to get-knowledge ; fills for each form the three knowledge unit variables
set c1 []
set c2 []
set c3 []
repeat possible-knowledge-space-2 ^n
[
    set c1 lput random 2 c1
    set c2 lput random 2 c2
    set c3 lput random 2 c3
]
set knowledge-list (list c1 c2 c3 )
end
to map-knowledge ; maps the knowledge, ie. creates a list of the bitstreams generated from applying the mapping functions to the knowledge units of the firm
map-product-id
set mapped-knowledge []
foreach item product-id mapping-function
[
    let dummy []
    foreach ?
    [  
    let temp-knowledge-item-address last ?
    let temp-knowledge-bit-address first ?
    set dummy lput item temp-knowledge-bit-address (item temp-knowledge-item-address
    knowledge-list) dummy
    ]
    set mapped-knowledge lput dummy mapped-knowledge
]
end
to map-product-id ; creates an integer based on the PIMF and the knowledge of the firm
set product-id []
let counter 0
foreach product-id-mapping-function
[
    set product-id lput item counter (item ? knowledge-list) product-id
    set counter counter + 1
]
let temp-id 0
set counter 0
repeat length product-id
[
    if last product-id = 1
    [ 
    set temp-id temp-id + 2 ^ counter
    ]
    set product-id but-last product-id
    set counter counter + 1
]
set product-id temp-id mod number-of-products
end
to create-global-needs ; creates a list of 1 and 0 of the length products X characteristics X bit length

set global-needs []
repeat number-of-products
[ let counter2 []
repeat number-of-characteristics
[ let counter []
repeat needs-length
[ set counter lput random 2 counter
]
set counter2 lput counter counter2
]
set global-needs lput counter2 global-needs ]
end
to determine-needs ; determines the needs of each consumer, depending on the degree of heterogeneity

set needs []
let counter3 0
let counter4 0
let counter5 0
repeat number-of-products
[ let counter2 []
let counter4 0
repeat number-of-characteristics
[ let counter []
set counter5 0
repeat needs-length
[ ifelse random-float 1 < consumer-heterogeneity [set counter lput random 2 counter][set counter lput (item counter5 (item counter4 (item counter3 global-needs))) counter]
set counter5 counter5 + 1
]
set counter2 lput counter counter2
set counter4 counter4 + 1
]
set needs lput counter2 needs
set counter3 counter3 + 1 ]
end
to go tick
if show-knowledge [visualize-knowledge]
set number-radials-product-1 count firms with [last-innovation = "radical" and
product-id = 0 ] 
set number-incrementals-product-1 
count firms with [last-innovation = "incremental" and product-id = 0] 
ask firms 
[ 
  set selling? false 
  set list-of-sales lput sales list-of-sales 
  if length list-of-sales > 5 

  [ 
    set list-of-sales but-first list-of-sales 
  ] 

  set sales 0 
  set buyers [] 
  set age age + 1 
  set last-innovation [] 
] 

ask consumers [set sellers []] 
compute-fitness 
R&D 
do-start-ups 
do-plots 
compute-resource 
end 

to visualize-knowledge; links all knowledge bits of a firm, e.g. produces 'knowledge triangles' 
; ask knowledge-bits [set hidden? true]; switched off for testing 

ask ihs [die] 
ask innos [set link-age link-age - 1 if link-age = 0 [die]] 
let firms-knowledge [] 
ask firms 
[ 
  foreach knowledge-list 

  let starter ? 
  set firms-knowledge lput ? firms-knowledge 
  foreach knowledge-list 

  if starter != ? 

  [ 
    ask knowledge-bits with [name = starter] 

    [ 
      ask knowledge-bits with [name = ?] 

      [ 
        create-ih-with myself 
      ] 
    ] 
  ] 

  ] 
] 

set firms-knowledge remove-duplicates firms-knowledge
foreach firms-knowledge
    [ if Member? ? list-of-knowledge
        [ ask knowledge-bits with [name = ?] [set_hidden? false ]
        ]
    ]
ask knowledge-bits with [count my-ihs = 0 ][ set_hidden? true ]
end
to do-start-ups; creates start-ups, if capitalism is off; firms will die if they are
not selling for more than 5 rounds
if Start-ups
    [ ask firms
        [ if Capitalism = false ; if capitalism is on, firms will die if they run out of
        resources.
            [ if sum list-of-sales = 0 and age > 5
                [ die
                ]
            ]
        ]
    ]
if ticks / 2 = round (ticks / 2 )
    [ create-firms 1
        [ set shape "factory"
            setxy random-xcor random-ycor
            set color blue
            if show-knowledge [set_hidden? true]
            get-knowledge
            map-knowledge
            set selling? false
            set sales 0
            set list-of-sales []
            set age 0
            set resource 2
        ]
    ]
end
to compute-fitness; compares the offered product of each firm with the demand of
consumers bit by bit. It simply counts the number of differences.
The firm with the lowest number will sell to the consumer
set average-fitness []
set average-fitness-product-0 []
ask consumers
    [ 
let current-product 0
repeat number-of-products
[  let best-fitness 0
  let best-firm []
  ask firms with [product-id = current-product]
  [  let fitness-temp 0
      let counter 0
      foreach mapped-knowledge
      [  set fitness-temp fitness-temp + length remove 1
        (  map [(?1 - ?2) ^ 2 ^ 0.5 ]
          ? item counter (item product-id [needs] of myself))
        set counter counter + 1
      ]
      if fitness-temp > fitness-threshold / 100 * possible-knowledge-space-2 ^n *number-of-characteristics
      [  if fitness-temp = best-fitness
         [  best-firm (turtle-set best-firm self) ]
      ]
      if fitness-temp > best-fitness
      [  set best-fitness fitness-temp
          set best-firm self ]
    ]
  ]
if best-fitness > fitness-threshold / 100 * possible-knowledge-space-2 ^n *number-of-characteristics
[  set average-fitness lput best-fitness average-fitness ]
if best-firm != []
[  if last-seller = nobody
     [  set last-seller [] ]
  if is-agentset? best-firm
     [  ifelse not (last-seller = []) and member? last-seller best-firm
        [  set best-firm last-seller ]
      ]
     [  set best-firm one-of best-firm ]
  ]
set sellers lput best-firm sellers
set last-seller best-firm
ask best-firm

[  
  set selling? true
  set sales sales + 1
  set buyers lput myself buyers
  if product-id = 0

  [  
    set average-fitness-product-0 lput best-fitness
    average-fitness-product-0
  ]
]

]  

set current-product current-product + 1

;show average-fitness-product-0
end

to compute-resource ; computes the resources based on the number of sales and the price of research. The prices of radical and incremental research are defined by the user.

if capitalism
  [  
    ask firms

    [  
      strategy = "radical"

      [  
        set resource resource - radPrice
      ]

      if strategy = "incremental"

      [  
        set resource resource - incPrice
      ]

      if selling? = true

      [  
        set resource resource + 2 * sales
      ]

      if resource <= 0 [die]
    ]

  ]
end

to R&D; defines two different research strategies.
let radical-threshold relative-radical-threshold * count consumers / 100
let incremental-threshold relative-incremental-threshold * count consumers / 100
ask firms
  [  
    set strategy "none"
    if sales >= radical-threshold and sales <= incremental-threshold
; If market share is below incremental threshold, firm will innovate
incrementally i.e. a piece of random length in the knowledge of a firm will
be replaced by a new, random bit stream piece (by the incremental
probability)
set strategy "incremental"
if prop-of-increm-R&D > random-float 1

[ set last-innovation "incremental"
let knowledge-item-number random length knowledge-list
let knowledge-item item knowledge-item-number knowledge-list
let old-knowledge knowledge-item
set knowledge-item replace-item random length knowledge-item
knowledge-item
random 2
if show-innovation and knowledge-item != old-knowledge

[ ask one-of knowledge-bits with [name = old-knowledge]

[ create-inno-to one-of knowledge-bits with [name =
knowledge-item]

[ set link-age 5 set color green
]
]
]
set knowledge-list replace-item knowledge-item-number knowledge-list
knowledge-item
map-knowledge
]}

if sales < radical-threshhold
[; if market share is below the radical threshold, one
of the knowledge units of a firm will be replaced by a random one (by the radical
probability)
set strategy "radical"
if prop-of-radical-R&D > random-float 1

[ set last-innovation "radical"
let knowledge-item-number random length knowledge-list
let old-knowledge item knowledge-item-number knowledge-list
let knowledge-item []
repeat possible-knowledge-space-2 ^n

[ set knowledge-item lput random 2 knowledge-item
]
if show-innovation and knowledge-item != old-knowledge

[ ask one-of knowledge-bits with [name = old-knowledge]

[ create-inno-to one-of knowledge-bits with [name =
knowledge-item]

]
set link-age 5 set color red

] ]

] set knowledge-list replace-item knowledge-item-number
knowledge-list
knowledge-item
map-knowledge

END

; computes resources for all firms depending on their R&D strategy and the respective prices set by the user

to do-plots
set-current-plot "number-of selling-firms"
plot count firms with [selling? = true ] / count firms
set-current-plot "average age"
plot mean [age] of firms
if length average-fitness > 1
  [ 
    set-current-plot "average fittness"
    set-current-plot-pen "average"
    plot mean average-fitness
    set-current-plot-pen "max"
    plot max average-fitness
    set-current-plot-pen "min"
    plot min average-fitness
  ]

set-current-plot "R&D"
set-current-plot-pen "incremental"
plot count firms with [strategy = "incremental" ] / count firms
set-current-plot-pen "radical"
plot count firms with [strategy = "radical" ] / count firms
set-current-plot-pen "none"
plot count firms with [strategy = "none" ] / count firms
set-current-plot "histogram-of-sales"
histogram [sales] of firms
set-current-plot "innovations"
set-current-plot-pen "radical"
set-current-plot "Average-fitness-product-1"
if average-fitness-product-0 != []
  [ 
    set-current-plot-pen "Average Fittness"
    plot mean average-fitness-product-0
    set-current-plot-pen "radical Inno"
    let counter count firms with [product-id = 0 ]
    if counter != 0
      [ 
        plot number-radials-product-1 / counter
        set-current-plot-pen "Incremental Inno"
        plot number-incrementals-product-1 / counter
      ]
set-current-plot-pen "number of Firms"
plot counter
]
end of code