The Network Dynamics of Financing Technological (R-) Evolution

The Case of Technological Change in the Renewable Energy Area

Ph.D. Dissertation

Daniel S. Hain

Dissertation submitted August 13, 2015

Thesis submitted:	August 13, 2015
PhD Supervisor:	Assoc. Prof. Jesper Lindgaard Christensen Aalborg University
Assistant PhD Supervisor:	Prof. Birgitte Gregersen Aalborg University
PhD Series:	Department of Business and Management, Faculty of Social Science, Aalborg University

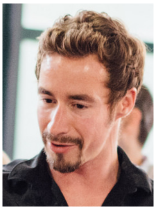
ISSN: xxxx-xxxx
ISBN: xxx-xx-xxxx-xxx-x

Published by:
Aalborg University Press
Skjernvej 4A, 2nd floor
DK – 9220 Aalborg Ø
Phone: +45 99407140
aauf@forlag.aau.dk
forlag.aau.dk

Printed in Denmark by Rosendahls, 2015

Curriculum Vitae

Daniel S. Hain



Daniel S. Hain is a researcher in the field of innovation and evolutionary economics, with the particular research interests in the fields of economic complexity and complex system analysis, network analysis, investor and research networks, the impact of private investments and public funding on innovation activities, the evolution of technology, and technology forecasting.

He is a (currently graduating) Ph.D. fellow at Aalborg University (Denmark) and associated with the "Innovation, Knowledge and Economic Dynamics" (IKE) research group, the "Danish Research Unit for Industrial Dynamics" (DRUID) society, and the "Global Network for the Economics of Learning, Innovation, and Competence Building Systems" (GLOBELICS). His Ph.D. project is part of the danish strategic research alliance on "Energy Innovation Systems" (EIS).

The papers written during his Ph.D. period got accepted for publication in the "Journal for Business Ethics" (JEB), "Journal for Evolutionary Economics" (JEEC), and are also to be found in the Springer conference proceedings for the annual conference on "SocioInformatics" (SocInfo).

During his Ph.D., he lectured on general macro- and microeconomics, statistics and econometrics, and the financing of innovation, supervised projects and theses on bachelor and master level.

As a part of his Ph.D. research, from January until July 2014 he was as a "Visiting Research Scholar" at Stanford University. There, he focused on deepening his knowledge in the fields of network analysis, complexity research, natural language processing, and the sociology of science.

He currently holds a M.Sc. in "Economics" from Aalborg University and a M.Sc. in "International Business" from the University of Hohenheim (Germany).

Prior he worked as a management consultant with focus on process optimization, supply chain management and absolved an university education in industrial engineering (Dipl.-Wirt.-Ing., german diploma) at the Unifersity of Stuttgart-Vaihingen / Stuttgart Media University, with special focus on process optimization and simulation, and embedded enterprise information systems.

Abstract

This Ph.D. thesis explores the complex interplay between finance and technological change. The duality between finance and technological change has long been recognized as a main driving force behind capitalist dynamics and economic progress. The search for new technologies is a risky and uncertain endeavor, especially for the ones leaving established technological trajectories and engaging in more radical forms of innovation. This search is dependent on a variety of resources, such as knowledge, infrastructure, equipment, and capital – which seldom can all be provided by any single entity. Consequently, it is well understood that innovation – a main driving force of technological change – is above all a social process, not happening in isolation but as the outcome of the interplay between multiple actors. In modern capitalistic economies, not only researchers, inventors, entrepreneurs and managers, but also their providers of capital are crucial participants in this process. In this thesis, I investigate how interaction and cooperation pattern among and between investors and innovators influence the rate and direction of technological change with respect to the characteristics of the technological system in which this change happens.

As a guiding case to answer this question, I mainly focus on investments in the renewable energy area, and the resulting transition of the energy system. Indeed, the interdisciplinarity of knowledge and resulting actor heterogeneity, the system character and complexity, and the high capital intensity of the energy area makes it an an interesting case to illustrate the complexity of financing technological change. However, even though the conditions appear to be unique in their combination, they stem from more generic problems, which can be observed in several other sectors. Consequently, the implications of this Ph.D. thesis, and the methods developed to derive them, are, *mutatis mutandis*, applicable in a variety of other technological systems.

In detail, I develop a guiding framework, where technological change can be explained as the outcome of interactions within and between (i.) the research space where technology is developed by research agents, (ii.) the intermediate technology space where a technological system evolves through the recombination and -configuration of its elements, and (iii.) the financial space where financial agents search for possible investment opportunities in technology space. The six core chapters represent research papers written with a variety of co-authors during my Ph.D. fellowship. The first two lay groundwork by discussing generic issues of research on the finance of innovation and technological change. All following four papers analyze separately a specific and important aspects of network or actor dynamics within or between the proposed three dimensions of technological change, and in combination attempt to enhance our understanding how technology evolves as the macro-outcome of micro-interactions of actors and entities within and along these dimensions. Where needed, chapters aim to establish an empirical or theoretical foundation for further analysis, or focus on analyzing the effects of different variables, illustrating or develop methods to do so. The empirical context of this work varies broadly, ranging from the cross-industry, equity investment, the smart-grid industry to the singularity movement. Some of the attempted contributions are empirical, some theoretical, and some are in method development. Yet, what all of them have in common is that they draw from system and complexity theory, envisioning technological change as the interplay between different subsystems, which are in turn populated by interacting agents or elements. Here, network theory and analysis provides the "glue" connecting these dimensions.

I provide evidence how network structures among investors – and with innovators – greatly influence the rate and direction of technological change, and how this influence varies with respect to different characteristics of technological systems. I thereby identify how investors via interaction and cooperation alleviate barriers associated with investments in innovation in complex technological systems – such as uncertainty, asymmetric and imperfect information, and bounded rationality. Further, I also demonstrate how targeted investments in technological change are able to influence the network structure among firms and researchers active in the innovation process. I thereby provide direct policy implications on how to facilitate the emergence of network structures among innovators and investors which are conducive for a certain desired rate and direction of technological change. Further, this thesis aims for an academic contribution by conceptualizing technological change in a Schumpeterian duality of micro-level interaction between investors and innovators, and demonstrating methods to conduct research on this interaction.

Aknowledgements

> “I find that a great part of the information I have, was acquired by looking up something and finding something else on the way.”
>
> – Franklin Pierce Adams

Knowledge discovery is rarely easy. Indeed, no research endeavor is the product of one person alone, so here I use the opportunity to thank the many people that have contributed to this research.

Above all, I would like to express my sincerest appreciation to my supervisors at Aalborg University, Professor Jesper Lindgaard Christensen and Birgitte Gregersen, for being great and inspiring mentors. I am also very grateful for the support of the whole IKE staff at Aalborg University, foremost Professor Bengt-Åke Lundvall and Esben Sloth Andersen.

I am also very grateful to have found a set of further wonderful and smart co-authors to complement this thesis in numerous ways, namely Roman Jurowetzki and Daojuang Wang (Aalborg Universty), Dr. Sofia A. Johan (York University - Schulich School of Business) and Elena Mas Tur (INGENIO, Universitat Politècnica de València).

I also want to thank the great scholars that also took their time to support me with very valuable feedback and discussions, foremost Professor Andreas Pyka (University of Hohenheim), Douglas Cumming (York University - Schulich School of Business) and Alex Coad (JRC-IPTS-KFG, Seville). I further owe a lot of my insights to the great scholars I was exposed to at my time as visiting researchers at Stanford University, foremost Walter W. Powell, Mitchell Stevens and Daniel McFarland.

Additionally, I would like to extend my acknowledgement to all my fellow Ph.D. students here at the IKE group for being supportive and cheerful, particularly my former officemates Juan Martin Carriquiry and Eunkyung Park.

Finally, having a great and supportive family helps as well in such times. Therefore, my sincerest appreciation to my loving parents and my wonderful little sister.

And finally, for all those I forgo o mention here, even though they deserve some credit for the work (I am sure I did)... feel very included here.

Preface

> "We have not succeeded in answering all our problems – indeed we sometimes feel we have not completely answered any of them. The answers we have found have only served to raise a whole set of new questions. In some ways we feel that we are as confused as ever, but we think we are confused on a higher level and about more important things."

– Earl C. Kelley

So, the dices are rolled. After three years, this Ph.D. project, my largest research endeavor so far, is coming to an end. What a journey. The extract of combined knowledge gathered during this journey is what you – dear reader – now hold in your hand. A little book of three-hundred -and-some pages. Was it worth it? Well, that is up to you now to decide. Yet, as evolutionary economists we like to not only judge things according to their outcome but rather the process that lead to them. And indeed, I can tell you this was a process of struggles and doubts, but also personal growth, insights and pleasure. Glad to have chosen this profession, I now realize how fulfilling it can be to dedicate all your effort to the enhancement of knowledge. On an individual level, i find this endeavor to have been highly successful, since my knowledge has indeed greatly expanded. On a higher level, I can just hope this thesis provides you some new insights helping you to make sense of our enormously complex social and economic system.

I am well aware that I offer little answers to all the questions I raise, yet hope the thoughts reflected in this thesis shed new light on what moves technologies, societies, and economies. If nothing else, it might – in line with one of my very favorite quotes to be found above – elevates our constant confusion as social scientists to some higher level.

I hope you enjoy reading this peace of work, which is very dear to me.

Daniel S. Hain
Aalborg University, August 13, 2015

Thesis Details

Thesis Title: The Network Dynamics of Financing Technological (R-) Evolution - The Case of Technological Change in the Renewable Energy Area
Ph.D. Student: Daniel S. Hain
Supervisors: Prof. Jesper Lindgaard Christensen, Aalborg University
Prof. Birgitte Gregersen , Aalborg University

The main body of this thesis consist of the following papers.

[1] Jesper Lindgaard Christensen and Hain, Daniel S., "Knowing where to go: the knowledge foundation for investments in energy innovation", *submitted for publication*, 2015.

[2] Daniel S. Hain and Lindgaard Christensen, Jesper, "The Small, the Young and the Innovative. A longitudinal analysis of constraints on external innovation financing", *submitted for publication*, 2015.

[3] Daniel S.Hain and Jurowetzki, Roman, "Incremental by Design? On the Role of Incumbents in Technology Niches - An Evolutionary Network Analysis" *Journal of Evolutionary Economics*, forthcoming.

[4] Daniel S. Hain; Johan, Sofia A. and Wang, Daojuan, "Determinants of Cross-Border Venture Capital Investments in Emerging and Developed Economies: The Effects of Relational and Institutional Trust", *Journal of Business Ethics*, forthcoming.

[5] Roman Jurowetzki and Hain, Daniel S., "Mapping the (R-) Evolution of Technological Fields – A Semantic Network Approach", in Aiello, Luca M. and McFarland, Daniel (Eds.), Social Informatics, Springer International Publishing, Social Informatics - Lecture Notes in Computer Science series, vol. 8851, pp. 359-383, 2014

[6] Daniel S. Hain and Tur Mas, Elena, “Technological Change and Investments on a Rugged Landscape – An Agent Based Simulation”, Conference paper: *DRUID Summer Conference*, Rome, June 2015.

Additional to the main papers, the following publications have been made.

[1] Daniel S. Hain; Buchmann, Tobias; Kudic, Muhamed and Müller, Michael “Exploring the Evolution of Innovation Networks in Science-driven and Scale-intensive Industries: New Evidence from a Stochastic Actor-based Approach” *IWH Discussion Paper 1/2014*, 2014

[2] Borup, Mads; Klitkou, Antje; Andersen, Maj M.; Hain, Daniel S.; Lindgaard Christensen, Jesper and Rennings, Klaus, “Indicators of energy innovation systems and their dynamics. A review of current practice and research in the field”, *EIS radar paper*, 2013

[3] Daniel S. Hain and Lindgaard Christensen, Jesper, “Scared Away? Discouraged Borrowers and Capital Market Information”, *Conference paper: ISBE, Winchester*, 2014

[4] Daniel S. Hain And Jurowetzki, Roman, “The Silicon Savanna - Local Competence Building and International Venture Capital in Low Income Countries - The Emergence of Foreign High-Tech Investments in Kenya”, *GLOBELICS Working paper Series*, 2015

[5] Letícia A. Nogueira; Hain, Daniel S. and Lindgaard Christensen, Jesper, “Greenagers out in town – The collaboration patterns of entrepreneurial, green firms”, *Conference paper: SBE special issue workshop: BORN TO BE GREEN: THE ECONOMICS AND MANAGEMENT OF GREEN START-UPS, Winchester*, 2015

This thesis has been submitted for assessment in partial fulfillment of the PhD degree. The thesis is based on the submitted or published scientific papers which are listed above. Parts of the papers are used directly or indirectly in the extended summary of the thesis. As part of the assessment, co-author statements have been made available to the assessment committee and are also available at the Faculty. The thesis is not in its present form acceptable for open publication but only in limited and closed circulation as copyright may not be ensured.

Contents

Part I

Introduction

Introduction

1 Objective and Motivation

Understanding the pattern of technological change is a crucial precondition to formulate meaningful long-term research and industry policy, and to secure sustainable long-term economic and social progress. This Ph.D. thesis attempts to enhance our understanding of a particular facet of this progress in capitalistic economies – the complex interplay between finance and technological change. Indeed, the duality between finance and technological change has long been recognized as a main driving force behind capitalist dynamics and economic progress (Schumpeter, 1934, 1942).

Yet, the search for new technologies is a risky and uncertain endeavor, especially for the ones leaving established technological trajectories and engaging in more radical forms of innovation. This search is dependent on a variety of resources, such as knowledge, infrastructure, equipment, and capital – which seldom can all be provided by any single entity. Consequently, it is well understood that innovation – a main driving force of technological change – is above all a social process, not happening in isolation but as the outcome of the interplay between multiple actors. In modern capitalistic economies, not only researchers, inventors, entrepreneurs and managers, but also their providers of capital are crucial participants in this process.

While we can draw from a large body of literature on how interaction between firms and other agents carrying out research influences the rate and direction of technological change, and how in return the characteristics of technologies feed back in the way how cooperation is organized, the same holds not true for the interaction between and among investors and innovators.

In this thesis, I investigate exactly this interplay according to the guiding research question:

How does interaction and cooperation pattern among and between investors and innovators influence the rate and direction of technological change with respect to the characteristics of the technological system in which this change happens?

2 Backgound – The Case of Renewable Energy

As a guiding case to answer this question, I mainly focus on investments in the renewable energy area, and the resulting transition of the energy system. Indeed, the interdisciplinarity of knowledge and resulting actor heterogeneity, the system character and complexity, and the high capital intensity of the energy area makes it an an interesting case to illustrate the complexity of financing technological change.

To create a truly sustainable energy systems, the challenges are indeed manifold. Progress is needed in a broad range of technologies to improve the way and increase the set of options as to how we produce, distribute, store, and use energy. This is the sphere of natural science, including engineers, computer science, and physics. Environmental consequences of our current energy system such as the massive emission of carbon-dioxide have to be analyzed and evaluated. This is the sphere of biologists and environmental scientists. Finally, these insights have to be transferred to action by specifying research agendas, allocating public R&D funding and promoting private investments in the development and deployment of key-technologies, establishing favorable interaction structures among the energy system's actors, and creating supportive institutions. This is the sphere of social scientists, one might argue particularly of us innovation researchers. To create meaningful advice in this process we face our own challenges, which are empirical as well as conceptual.

2.1 Relevance and Case-Motivation

Our new generation undeniably lives in a world where economic growth and the associated use of resources will reach hard physical constraints. Against the background of an increasing scarcity of fossil energy sources and accumulating negative environmental effects of CO_2 and other emissions, the development towards a sustainable, and environmental friendly economy has become the major challenge our modern society has to face. Its severity reveals that incremental, as well as isolated solutions, will not be sufficient; the world is in need of substantial changes, involving all parts of contemporary economy and society. Accounting for more than 80 percent of global CO_2 emissions and confronted with peaking oil and coal (IPCC, 2007), the fundamental transformation of the energy sector is of particular importance. However, the development of the green economy also offers potentials for national growth and propensity (Jaeger et al., 2011).

2.2 The system character of the energy sector, and its actor heterogeneity

Yet, financial markets are far from maturity regarding the financing of innovation in renewable energy and indicate structural problems, as well as the lack of a proper institutional setup, which hampers the ability to properly respond to some critical characteristics of the sector – namely high technology as well as policy risks (Astolfi et al., 2008), the immense capital intensity (Burer and Wustenhagen, 2009), and long term perspective of investments (Kenney, 2011). Up to now, there is surprisingly little known about the complex systematic nature of renewable energies – especially when it comes to the finance of innovation. Even though there exists a large body of literature from the strand of environmental economics discussing the static efficiency of different financial measures and incentives,[1] literature falls surprisingly silent when it is about dynamic efficiency and future oriented investments in innovative activity. Owing respect to the pivotal importance of finance to a smooth functioning of modern economies (Rajan and Zingales, 1996), there exists a strong immediate need to address this gap.

However, understanding investments in the energy sector requires understanding its distinct characteristics (Grubb, 2004). The first such feature is that there is a high degree of system and infrastructure character. The production, innovations, and technologies in the sector are often connected to and dependent on other, complementary elements and technologies in the energy sector. Consequently, changes in one part of the sector are often linked to changes in other parts of the sector. In many respects it is possible to talk about “energy systems” rather than just “sectors”.

[1]Consider Popp et al. (2009) for a exhaustive summary of more traditional economic approaches which, to be fair, at least partially take exogenous technological change into consideration.

This energy system, cutting through many different industries, shows a huge variety of involved actors with idiosyncratic rationales. First, the companies within the sector and the way innovation is exercised are quite heterogeneous. While some industries such as windmill production have already reached a high degree of maturity and are dominated by multinational enterprises (MNE)[2] and innovation manifests in a more incremental way, other industries and technologies such as hydrogen, full cells, smart grid and energy storage solutions are still in experimental phases, dominated by entrepreneurial activity and offering potential for the futures disruptive innovation. Where in some cases both types of innovation dynamics, namely the Schumpeterian mark I (Schumpeter, 1934) and mark II (Schumpeter, 1942), peacefully coexist(as described by Winter, 1984) in other cases inertia and traditionalism of incumbent firms and regulatory bodies[3] and normative stickiness lead to serious barriers for technological regime shifts (Tsoutsos and Stamboulis, 2005). Also the RE investors' landscape is much broader that in most other sectors. Besides traditional R&D funding and financial intermediaries such as venture capital, non-profit organizations, large institutional investors, private and public project developers, *et cetera*, are heavily involved in determining the amplitude and trajectory of futures research and innovation.

Energy innovations are often interwoven with other parts of the system, in the sense that, for being successfully taken to market, solutions in renewable energy require integration with other elements in the energy system. They are also said to involve more complex knowledge bases compared to most other innovations, indicating a broad need for cooperation and interaction among a broad set of actors active in the system. Indeed, in another research project (cf. Antunes Nogueira et al., 2015) we find firms in the danish renewable energy sector to show a roughly double cooperation intensity and diversity with external partners than their counterparts in other industries.

In conclusion, the world of renewable energy is vast and diverse, stretching over huge institutional, social, organizational and cognitive distance between the involved actors. Social, economic, and environmental pressure calls for fundamental changes in pace and direction of the sector's development, where traditional economics is very limited in providing guidance.

[2]For instance. the two biggest Danish windmill producers, Vestas and Bonus/Siemens, accounted for around 99 percent of installed capacity in 2004 (Lewis and Wiser, 2007).

[3]To give an example, utilities can be seen as one of the most traditional firms on markets in general, what often leads to a general adverseness against change in general, may it be organizational, technological or whatever. They are also often willing to exercise their influence on the market and regulatory bodies to prevent these kind of changes.

The heterogeneity and complexity of the energy system result in intense and broad and intense cooperation and interaction pattern among these heterogeneous actors.

2.3 The danish case

Even though there exists a general awareness of these facts, national governments around the world show varying ambitions and efforts towards the creation of sustainable energy systems. With the highest worldwide share of renewable energy in domestic generation, a strong national knowledge base, and ambitious targets for the future, Denmark can be seen as one of the pioneering countries in this field. In his opening speech to the parliament in October 2006, the Danish Prime Minister announced the long-term target of total independence of fossil fuels and nuclear energy by 2050. A large research project conducted by the Danish Association of Engineers (IDA) confirmed the physical and technical long-term feasibility of an energy system completely based on renewable resources (Lund and Mathiesen, 2009). Yet, tremendous and comprehensive changes throughout the whole economic and social system and its institutions, as well as the supporting infrastructure, will be necessary. Among others, a steady and high rate of technological progress in a variety of established and emerging technologies represents a necessary condition for feasibility.

In the latest 2014 danish community innovation survey (CIS), 12% of firms that planned to be active in energy innovation projects reported that they encountered financial barriers to do so. About 70% said this barriers where too severe to overcome, even in a country with a generally high acceptance of renewable energy (RE) technologies and board investment and financial support schemes by the state. This measure can even be seen as a conservative estimate, since it does not include firms discouraged to aim for innovation activities entirely, in anticipation of financial barriers. It also does not consider firms and other actors in the energy system with the potential to contribute to technological change towards a sustainable energy sector, but no incentive to do so. In short, there is ample demand to identify mechanisms conductive for the development of renewable energy technologies. Public and private finance is a likely candidate to be one of the driving forces of a sustainable transition, if understood well.

Theoretical Building Blocks: Complexity, Networks and Technological Change

This Ph.D. thesis is inspired by multiple streams of literature, namely classical finance theory, industrial dynamics, innovation systems, evolutionary economics, the sociology of science, network and complexity theory. While specific literature reviews on the topic under research are provided in the corresponding papers, I will still use this chapter to introduce these core concepts, which are cross-cutting through the whole thesis.

Finance, Investors, and Technological Change

The finance of innovation, and the behavior of different types of investors, such as banks, venture capitalists, or government authorities allocating public funding, lies at the very core of this thesis. In the following, I will briefly summarize some key insights from a long tradition of finance research from various streams. Firstly, I elaborate on a very central theme in finance literature – and also this thesis – which is said to be responsible for the major frictions on capital markets – asymmetric information. I proceed with elaborating on the interplay between finance and technical change on a macro-level, and arrive at the more micro-level issues of financing innovation – the driving force of technological change. In the following, I firstly discuss the role of the state in financing technological change, and close with expanding on the decision making process of – mostly private sector – investors.

Finance basics - Financial constraints and asymmetric information

Traditionally, financial constraints are said to stem from asymmetric and imperfect information. This leads to a highly perceived uncertainty and the need for banks and other financiers to gather firm specific soft and private information for a proper assessment of creditworthiness. Because of this, financiers employ different strategies in their screening procedures to deal with this problem. These strategies include repeated contracts and relationship banking, specialization, monitoring, independent auditing and screening, milestone financing, and collateral. However, not only are these measures costly to the financier, they are also insufficient to reveal all relevant information or compensate for the remaining information. Financiers are therefore particularly skeptical at the outset when assessing proposals from firms that either have characteristics that amplify the lack of or asymmetries of information and/or in the past have been shown to make up a disproportionate share of defaults. As a result, some firms with certain sets of characteristics appear to be consistently penalized by capital markets; namely those who are young, small, innovative, and mainly based on intangible assets (Beck and Demirguc-Kunt, 2006; Canepa and Stoneman, 2008; Carreira and Silva, 2010, e.g.). At the same time, exactly these firms are repeatedly mentioned as those who are meant to carry much of the future growth of the economy, both in terms of employment growth (Acs et al., 2004) and static and dynamic efficiency of the economic system (Audretsch, 1995, 2006).

Finance and technological change

The pivotal role of finance in facilitating innovation and propelling technological change is already emphasized in the work of Schumpeter (1942), who claims innovations based on credit creation as the force behind capitalist dynamics. However, it has also been recognized that investments in innovation appear to be substantially different from other forms of investments (Hall, 2010; Hall and Lerner, 2009). Early work (Arrow, 1962; Nelson, 1959) commonly associates innovation and technological progress with investments in R&D and also argue that knowledge spillovers lead to incomplete appropriation of their results. This decreases firm/investors incentives to carry out such investments. Subsequent research during the last decades has provided manifold examples of how the design of financial systems (Dosi, 1990), the behavior of investors on financial markets (Perez, 2002, 2004, 2010), public funding (Mazzucato, 2011), and firm level resource allocation (Tylecote, 2007) massively impact the rate and direction of technological change. Yet the vast majority of research on technological change focuses on the behavior of researchers/inventors and innovators/entrepreneurs while neglecting financial agents.

The finance of innovation

Investments in innovation projects appear to be substantially different from other forms of investments. Early work (Arrow, 1962; Nelson, 1959) commonly associates innovation with investments in R&D and argue that knowledge spillovers lead to incomplete appropriation of their results, thus decreasing decrease firm incentives to carry out such investments.

A second major argument rests on the lack of and unequal distribution of information. The innovation process is inherently characterized by uncertainty (Dosi and Orsenigo, 1988) but even on a more general level, the financing process has been dealt with as one of asymmetric information, leading to credit rationing. The separation of ownership and management has added to this in the form of principal-agent problems (Brealey et al., 1977; Myers and Majluf, 1984; Stiglitz and Weiss, 1981).

When R&D projects are involved the asymmetries in information may cause the markets to malfunction and impose a premium on external finance thus rendering retained earnings relatively more important for financing of innovation projects. Ways of mitigating these problems include repeated interactions and reputation Hall (2010).

Innovation processes are reliant upon and embedded in human capital, which is often volatile and not easily maintained in the firm. The intangible nature of many innovation processes, and the fact that they have long time lags from initiation to returns, means that financiers are faced with projects where they have poor possibilities to estimate the returns, and poor options to cover the risk by way of collateral. It is likely that these problems are amplified in the case of young, small firms based primarily on knowledge.

The role of the state and public funding of research and development

The direct funding of R&D in selected technologies of interest represents an integral component of modern innovation policy. Given the proper institutional setup it offers a powerful tool to directly steer rate and direction of research activities (Pavitt, 1998). Indeed, throughout history most technological revolutions which fundamentally changed our society, such as rail roads, modern ITC and biotechnology initially where triggered by massive government funded research programs before spilling into the private sector (Mazzucato, 2011; Perez, 2011). However, in general, our understanding of how governments interact with the system they try to affect is limited (Jaffe, 2008), and in particular, the efficiency of public R&D funding is still under heavy discussion.[4]

Economic theory suggests the direct funding of R&D by the state as a mean to: (i.) Prevent market failure associated with the characteristics of knowledge production (Arrow, 1962) and uncertainty of innovation (Knight, 1921), which otherwise would lead to an underinvestment in innovative activities on a general level.(ii.) Promote a development in direction of technologies with large expected social returns but at the current state lacking economic returns (Klette et al., 2000). (iii.) Securing the presence of a broad and diverse set of technological opportunities (Freeman, 1974). (iv.) Correcting system failure by generating networks among firms, societal organizations, and knowledge institutions (Carlsson and Stankiewicz, 1991).

Investment decision making, incomplete information and uncertainty

While in standard finance theory investors primarily aim to optimize their risk-adjusted returns and do not care about much else, reality has proven a convenient assumption for economic modeling as oversimplistic in a couple of ways. First, not only the average, but also the variance of returns matter. Assuming investors *per se* to be risk averse, given the same risk adjusted returns they will tend to choose the investment with less variance. Second, different investors will have different risk preferences and specialize on certain risk-return-variance levels. While institutional investors such as pension funds usually show a very low risk tolerance and require only modest returns, venture capitalists invest in highly risky targets but therefore demand extraordinary returns.[5] Third, a long tradition of research on behavioral finance tells us that this risk/return assessment is less of an objective optimization process by fully rational agents, but rather a heuristic one by agents acting under "bounded rationality" (Simon, 1955). Since the set of information needed to fully assess an investment's risk adjusted returns in most cases is incomplete and the agents processing power is limited, their

[4]For an overview of the academic discourse regarding the impact of public R&D funding consider David et al. (2000); Klette et al. (2000)

[5]In later chapters, I will also challenge this assumption, at least on theoretical ground.

judgment will often be based on simple heuristics, rules-of-thumb, and intuition (Tversky and Kahneman, 1974). Further, this judgment is also subject to a set of cognitive biases (McFadden, 2001) caused by the agents beliefs, historical experiences, and social influences. Thus, investment decisions are made based on "perceived risk", which will differ between agents according to their existing knowledge, available information, and cognitive biases. Besides optimizing perceived risk-adjusted returns of their portfolio, some investors in RE also integrate social, environmental, and ethical considerations into their decision making (Renneboog et al., 2008). Moreover, financial constraints are in the financial literature said to stem from problems derived from asymmetric information between borrowers and lenders (Akerlof, 1970; Myers and Majluf, 1984). Because energy systems are highly integrated and interdependent, these problems are likely to be multiplied.

Even though this assessment is still subject to imperfect information and cognitive biases, it will become more precise when investors undertake the effort of gathering a more complete set of information on investment and context, and when applied heuristics improve with increasing investment experience and knowledge relevant for the particular investment. Therefore, capital markets are characterized by a division of labor and specialization which is expedient when investors need to cope with complex and asymmetric information in the market. Investors might specialize on investments in firms of certain characteristics (start-ups, mature firms), deployed technologies (ICT, biotech, RE), asset classes (VC, PE, loans, project finance), risk profiles (low, high), *et cetera*. Specializing on one or more of these investment characteristics results in a particular set of relevant investment targets and information needed for the assessment.

Scientific and Technological Paradigms in Social Science

In neoclassical economic theory, technological change is commonly envisioned as an equilibrium shifting exogenous shock or as something subject to a production function with a determined relationship between inputs such as R&D spending, and outputs such as patents or sales with new products. A more modern understanding depicts innovation inherently as happening endogenously to the system it is embedded in. The system's components are understood as interdependent among each others as well as with elements outside the system's boundaries (Carlsson and Stankiewicz, 1991; Freeman, 1987; Lundvall, 1992; Nelson, 1993) or other.

In the long tradition of research in social science since (Kuhn, 1962), technology primarily exists to fulfill or support some societal functions through direct application or indirectly through derived products. It is thus always embedded in and framed by a societal, political, and organizational context, which co-evolves with it (Kaplan and Tripsas, 2008). Work by sociologists within the Science, Technology and Society (STS) tradition has produced many concepts and valuable insights into processes of systemic technological change Bijker et al. (1987); Hughes (1987). The seminal work of Kuhn (1962) illustrates how science develops in a path dependent manner within a *scientific paradigm* – which can be understood as framework of accepted concepts, results, and procedures within which subsequent scientific work is structured. The progress of normal science is usually bond by the structure of problem-solving processes within such paradigms, hence, usually focuses on incremental extensions of relationships, the refinement of agreed ones, and the increase of measurement precision.[6] However, discoveries fundamentally contradictory to what is universally accepted can sometimes lead to epistemological paradigm shifts which Kuhn (1962) labels as "scientific revolution".[7]

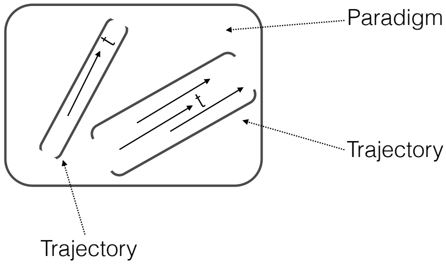
Since scientific and technological development have always been closely linked, we similarly understand a technological paradigm as "*a set of procedures, a definition of the relevant problems and of the specific knowledge related to their solution*" (Dosi, 1982). *Technological trajectories* here represent pathways spanning across the technological space delimited by the paradigm Dosi (1982), focusing the problem solving process over time around one possible configuration of technologies as illustrated in figure 1.

While such relevant problems are formulated in a societal discourse, the selection of procedures to address them are determined by technological and economic trade-offs. The problem solving process towards more advanced solutions usually unfolds gradually; yet sometimes significant technological discontinuities punctuate a trajectory, leading to a technological revolution (Perez, 2010) that alters a paradigm's internal logic and replaces existing trajectories in an act of Schumpeterian creative destruction (Schumpeter, 1942). The result of such a development – a technological system – can also be un-

[6]As at its time famously claimed by Lord Kelvin: "There is nothing new to be discovered in physics now. All that remains is more and more precise measurement."

[7]Traditional examples are the shift from the Maxwellian electromagnetic worldview to the Einsteinian Relativism in natural science, or in social science the Keynesian Revolution over orthodox neoclassical economics

Fig. 1: Technological paradigms and trajectories



derstood as a complex system with a number of elements that collectively fulfill one or several goals (Simon, 1969).

Existing empirical work to map and analyze technological chance can be broadly divided in three strands. Research in STS tradition often relies on case studies, including detailed description of the complex multidimensional setup around the studied technology, and sheds light on the variety of factors that can influence and shape its development (eg. Bijker et al., 1987). A stream of more positivist research in the fields of industrial economics and sciencometrics is primarily based on patent and scientific publication data as an approximation for technological development. Research so far mostly incorporates patent data as aggregated numbers to explain differences in scale Pavitt (1982), or in a network representation to explain structural differences (Fontana et al., 2009; Verspagen, 2007) in the development of technologies across countries and industries. Patent data has also been used to study invention as a recombination process (eg. Fleming and Sorenson, 2001). Most recently, social scientists have also started to deploy methods from the fields of computational linguistic and NLP to advance empirical research on the development of science and technology (DiMaggio et al., 2013; McFarland et al., 2013; Mohr and Bogdanov, 2013; Ramage et al., 2009). In their essence, such linguistically informed methods are capable of identifying patterns of language usage in large bodies of text and communication. They range from simple measures of word co-occurrence across documents, corpora, and over time Chen et al. (2012a,b), to complex linguistically informed probability model (Hall et al., 2008; Nallapati et al., 2011; Ramage et al., 2010) and dynamic technology networks (Jurowetzki and Hain, 2014).

Complexity and Technological Change

Framing technological change as happening within a complex technological system also calls for a discussion on the research on complexity in general, and in particular economic complexity. After doing so, I will expand further on a analytic tool as well as theoretical concept in complexity research which has proven to provide powerful implications for technological change – namely the NK model and associated fitness-landscapes.

Economic complexity

Social, technological, biological, and information systems all share, if anything, the characteristic of inherent complexity (Simon, 1991). The energy system, crosscutting social, technological and economic space, is no exception. As the "language of complexity", such systems are often described as networks that have a topology of interconnected elements combining organization and randomness (Boccaletti et al., 2006; Newman et al., 2006). Complex network analysis aims to understand how large networks of interacting dynamic systems behave collectively given their individual dynamics and coupling architecture (Strogatz, 2001). Framing relations and interactions as complex networks has also brought a fresh perspective to most branches of social science, including economics. Nowadays there are plenty of examples of how the logic and methodological toolbox of complex systems and network analysis can be deployed to understand economic development (Hausmann and Hidalgo, 2011; Hidalgo et al., 2007; Hidalgo and Hausmann, 2009), international trade pattern (Garlaschelli and Loffredo, 2005; Serrano and Boguñá, 2003), instability and systemic risk on derivative (Battiston et al., 2013; Roukny et al., 2013) and interbank loan (Markose, 2013) markets, banks credit (Uzzi, 1999; Uzzi and Gillespie, 2002) and venture capitalists investment (Bygrave, 1987; Hochberg et al., 2007) allocation, firms' access to external finance (Manolova et al., 2013), *et cetera*.

Fitness Landscapes and the NK-Model

To map and analyze selection processes as stochastic combinatory optimization in complex systems, in this case, how technological change by the way technologies within a larger technological systems are related to each others, the concept of "fitness landscapes" has proven useful. In its core, such a landscape represents a multidimensional mapping of components with attributed states of solution parameters to some measure of performance representing an elements fitness (Kauffman, 1993). In this fitness dimension, the landscape shows high performance "peaks" as well as low performance "valleys", where the peaks can be understood as the "evolutionary frontier" – the highest reachable level of a certain evolutionary path with respect to relevant environmental conditions. In the classical model proposed by Kauffman (1993), biological evolution of complex organisms, in which the functioning of genes is interdependent, has been analyzed as "hill-climbing" activity on NK fitness landscapes through random mutation and natural selection. Since the components are epistatically related, their fitness depends not only on their own states but also the "interaction" with their neighbors. The systems complexity is determined by the number of its components and their degree of epistasis, and manifests in the "ruggedness" of the landscape (Levinthal, 1997). Simple systems with a small set of components and/or low epistatic relations among them correspond to smooth landscapes with a few evenly distributed peaks, whereas complex ones correspond to a landscape with many unevenly distributed peaks of varying height. A main insight derived from such models is the efficiency of different evolutionary processes. With increasing complexity and associated ruggedness of the landscape, it becomes more and more unlikely that pure local selection will lead to globally optimal outcomes but rather to a lock-in into locally optimal *evolutionary pockets*.

This evolutionary metaphor has also been adopted to mimic research strategies of firms, concluding that with increasing complexity of the technological/scientific paradigm one is operating in, the more important exploration oriented research strategies become in contrast to local incremental exploitation of already existing solutions (March, 1991). It is further highlighted that increasing interdependence between technologies makes it very hard to integrate them in existing systems (Fleming and Sorenson, 2001). Indeed, modern technological systems appear to develop towards increasing epistasis, making outcomes of recombinatory processes such as R&D activities harder to predict. In order to understand innovation activity in many technological fields, it thus becomes important to understand the dynamics of these recombination which happen on large scale and with increasing pace. In the current energy system, for instance, the successful development of potential new energy sources is highly dependent on how their characteristics, such as their load fluctuation profiles, interact with existing energy production, transmission, and storage infrastructure. Consequently, the *ex-ante* prediction of research outcome in this area appears to be impossible without immense technological knowledge, a fact that daunts many financial agents to invest in emerging renewable energy technologies (Kenney, 2011).

While the chapter C is inspired by this concept, it becomes an integral part of chapter E and F. In chapter E I take up the task to map recombinatory processes in technological systems in a network representation, where we focus on the role of what we call "interface technologies" acting as coupling devices between formerly unconnected technological fields. An equivalent in the energy sector would be smart-grid technologies and the underlying ICT infrastructure, which ease the communication between energy production, storage and consumption, thereby offering a variety of technological possibilities. In chapter F I explicitly model the "search for investments" by financial agents inspired by selection processes on fitness landscapes. Since the energy system is known to be highly complex, diverse and interdependent, the corresponding technology landscape can be assumed to be equally "rough". Therefore, we explore how differences in investor population and their information sharing infrastructure - their network - impacts investments in technological change on flat versus rugged landscapes.

Research Networks and Technological Change

Previously I illustrated how complexity theory, in particular the concept of "fitness landscapes", can be leveraged to map and analyze technological change. I discuss how one can envision and analyze technological change as happening in a self-organizing system in technology space, orthogonal to other dimensions. I furthermore provided some examples as to how the research space and its population interacts with technology space by searching for performance improvement on a given landscape. Here, I will briefly review the rich body of literature on research and innovation networks, dealing mainly with the question of how particular cooperation pattern between firms or individuals emerge and how their structure affects innovation activities.

Research on cooperation of individuals and groups and their effect on their activity has a long tradition in social science. Ranging from seminal work by Simmel (1955) to Merton (1957), Granovetter (1973), Burt (1992) to recent work, it is well understood that the behavior of individuals and organizations is strongly affected by the way how they relate to and interact with larger collectives.

Nowadays it is well perceived that invention and innovation - the essence of technological change - is above all a social process not happening in isolation (Powell et al., 1996). A large body of literature from all strands of social science - economics, organizational and management studies, sociology, psychology, economics *et cetera* - offers various and nuanced insights on why and how firms and individuals draw a fair share of their input for the development of novelties from their network.

During the early 1990^s, scholars in management and organizational science started to focus on the importance of internal (*knowledge-based view:* eg. (Grant, 1996; Kogut and Zander, 1992; Spender and Grant, 1996)) and external (*network-based view:* eg. (Lavie, 2006)) knowledge stocks accessed via alliances (Grant and Baden-Fuller, 2004) to develop dynamic capabilities (Teece et al., 1997) and maintain a sustainable competitive advantage (Dierickx and Cool, 1989). Around the same time, economists started to embrace systemic approaches to the economy in general, and technological change in particular (Freeman, 1987; Lundvall, 1992; Nelson, 1993). Here, economic development is envisioned as the outcome of the interaction between various subsystems and embedded heterogeneous economic agents (Hanusch and Pyka, 2007; Pyka, 2002). Naturally, such a line of thought provides a fertile ground for network theory and analysis.

Since then, cascading research has created awareness as to how a firm's strategic positioning in interorganizational networks affects its innovative performance (e.g. Baum et al., 2000; Fleming et al., 2007b; Powell et al., 1996; Stuart, 2000). Not only the firm-centered ego-network positions but also the overall typologies of large-scale innovation networks have been shown to affect the innovative performance of firms (Schilling and Phelps, 2007) as well as entire networks (Fleming et al., 2007a) and regions (Fleming and Frenken, 2007; Saxenian, 2001).

Research also shows that networks of innovators are, like most other social networks, by no means static constructs in time and space, but rather constantly rearranging (Doreian and Stokman, 2005; Glückler, 2007; Powell et al., 2005), hence call for more dynamic and evolutionary approaches in empirical innovation network research (e.g. Ahuja et al., 2007; Cantner and Graf, 2011). Recent studies provide sound reasoning and empirical evidence as to how cumulative and path dependent forces strongly influence the actor composition, structure, and outcome of networks. If the current network structure impacts its possible future development, the network evolution becomes a path dependent and endogenous process (Glückler, 2007; Kilduff, 2003). Existing ties often tend to become more persistent over time (Burt, 2000), and preferential attachment makes the likelihood of creating new ties influenced by the actors stock (Barabâsi et al., 2002), leading to a process of structural reinforcement (Gulati, 1999). These findings also suggest that - as in every complex system - the development of such research networks is very sensitive to internal and external initial conditions such as heterogeneity of the industry structure or actor strategies. On these topics I will elaborate more in chapter C and chapter F.

Sociological, bibliometric, and scientometric research has produced a vast bulk of literature analyzing knowledge exchange among researchers, both within and across individual companies and academic research groups (e.g. Zucker et al., 1995), and investigating social networks of academic scientists (e.g. Melin and Persson, 1996; Newman, 2004). Recent research in this field is especially interested in the emergence of small world structures among academic cooperation (e.g. Wagner and Leydesdorff, 2005). These studies usually exploit information on co-authorship of scientific papers.

Scholars focused on cooperation among firms mainly come from the strand of strategic management. They analyze research and product development alliances with particular interest in their general rationales, their social (Gulati, 1995) and governance structure (Rowley et al., 2000), resulting knowledge flow and technology transfer among participants (Giuliani, 2007; Powell et al., 1996). Data hereto is mainly derived from large scale surveys among firms in a specific sector, or literature-based datasets.[8]

Another stream of scientific cooperation in industry an academia focuses on co-inventions by utilizing information contained in patent data. Singh (2005) reports especially social proximity as an important driver of patent-cooperation networks, and resulting knowledge flows. Fleming and Frenken (2007) and Fleming et al. (2007a) investigate the evolution of inventor networks in the Boston and Silicon Valley area, where they illustrate in both cases the phase transformation of globally sparse structures with a high share of isolated networks to one gigantic main component with small world properties, where some key actors bridge formerly unconnected clusters. They also provide anecdotal evidence, as to how path-dependencies brought these actors in their key positions.

Studies of network patterns based on the joint cooperation in public funded research projects are rather scarce. Very early, Sharp (1991) and Mytelka and Delapierre (1987) demonstrate the important role of research funding in establishing research alliances and networks in the European electric industries. Van Rijnsoever et al. (2012) investigate the network structure that emerged in the recent Dutch electric vehicle subsidy program, raising the question of how the actors' network position influences their probability of a successful grant application. To the best of my knowledge,Salerno et al. (2010) firstly

[8]Such as the MERIT CATI database on interorganizational strategic alliances (see Hagedoorn, 1990, and subsequent publications).

suggests the analysis of public funded R&D networks as valuable method for policy evaluation and technology forecast. Following this emerging idea, Mogoutov et al. (2008) combines the analysis of patent, publication, and public funded R&D projects, where they demonstrate the important role of the latter in linking the former two.

However, it is also recognized that on it's own, all of these data sources are likely to underestimate knowledge transfer and research cooperation in reality, which takes places in various formal as well as informal dimensions (Fleming et al., 2007a; Murray, 2002). Furthermore, cooperation between academia and industry appear to underlie a very distinct logic and incentive structure, which cannot be fully captured with one indicator. Recently, with combining co-authorship and co-invention data, scholars started to investigate how the two realms of academic science and industrial research are connected. Indeed, even though the social structure and incentives of *academic science* and *commercial technology* appear as rather distinct, this stream reveals first evidence of co-evolutionary processes to be at work. Murray (2002) opens this field with proposing a novel methodology to analyze these developments by using patent-publication pairs in the field of biomedicine. Even though not able to establish a predictable relationship, she provides plenty of anecdotal evidence regarding the importance of key-scientists to connect both realms. Bonaccorsi and Thoma (2007) investigate the performance of co-inventions explained by additional cooperation in scientific publication in the emerging field of nanoscience and technology. They report that patents filed by inventors which also co-author together tend to outperform others in terms of patent quality. They attribute this act to human capital and institutional complementaries at the intersection of science and business. Recently, Breschi and Catalini (2010) conducted a large scale analysis of European and U.S. American academia-corporate networks in three science intensive fields, i.e. lasers, semiconductors, and biotechnology, to assess the extent of overlap between the two communities. Their findings are that, on the individual researcher level, the connectedness among scientists and inventors is rather large. This highlights, again, the importance of certain persons which are prominent in both worlds and act as gatekeepers. They furthermore demonstrate that the connectedness of both spheres may be highly underestimated by only considering either co-author or co-patent networks.

Most work presented up to now is of a static nature and analyses social networks in research at a given point of time, while a few (e.g. Fleming et al., 2007a) choose a longitudinal approach. However, there exists a growing awareness of co-evolutionary mechanisms driving the development of multilevel networks such as research cooperation (e.g. Ahuja et al., 2007; Breschi and Catalini, 2010; Murray, 2002). However, analyzing evolutionary developments also call for new methods able to capture them. Just recently, researchers responded to this challenge with applying more dynamic and endogenously driven models to the context economic cooperation in general, and research cooperation in particular. To the best of my knowledge, Van de Bunt and Groenewegen (2007) firstly introduced dynamic actor-oriented to analyze endogenous effects in cooperation pattern of the genomics industry – where they report strong preference to form alliances with high-status partners. At the context of the project-based film industry Ebbers and Wijnberg (2010) try to disentangle reputation and network position effects where they report weak evidence that actors tend to team up with partners of equal reputation. Recently, Fischer et al. (2012) provided the first evidence in the Swiss telecommunication sector how regulatory changes – here the liberalization of the sector – lead to a endogenous reconfiguration of cooperation pattern. Finally, Kronegger et al. (2012) applies dynamic agent based models to scientific networks in the Slovenian research community. Combining a graph-theoretical perspective with the sociological concept of accumulated advantage, they attempt to explain which mechanisms drive the observed emergence of small worlds, but are ultimately not able to provide an unambiguous answer.

To sum up, network theory and analysis has proven to be a powerful approach to analyze and understand how the topology of research and innovation network influences research outcomes, and how and why they develop over time. Innovation is foremost a social process, and the increasing depth of knowledge in specialized disciplines makes cooperation and the associated flow of knowledge and ideas vital. With increasing complexity and interdisciplinary of a technological system, there is also an increasing need to cooperate and integrate inputs from distant knowledge bases, which appears to be particularly true for the energy system. Indeed, in the latest Danish CIS, firms engaged in innovation activities in the energy sector across the board show almost double cooperation rates compared to other innovators.

Industry and technology cycles and the finance of innovation

Without the commitment of financial resources, ideas remain ideas, independent of their potential. Surely, depending on the capital intensity of the technology, one can develop ideas and invention so far with a minimum commitment, as is the case with classical garage inventions. However, this can only go so far, since a fair share of progress is usually achieved by the testing of such inventions in real life situations where technological and economic properties can be gradually improved. To gain legitimacy and ease the way to commercialization, it often is necessary to demonstrate the feasibility and functionality of the invention in a real-life setting of appropriate scale. Finally, to become an innovation, the invention has to be introduced to the commercial market, with all the costs associated. During this process, capital requirements increase and at one point sooner or later exceed the amount that can be stemmed without an influx of external financial resources. Consequently, understanding decisions of investors to allocate investments in the exploration, development, demonstration and deployment of novel technologies becomes integral to understand and explain technological change. Figure A.3 in chapter A depicts a stylized linear model of technology development, including typical characteristics and involved research and financial agents.

Applying such a life-cycle perspective on technology development including different types of agents, investments and investors offers valuable insights. First, mismatches between actor and technology characteristics with investor capabilities and preferences can cause financial bottlenecks at any of these stages and seriously jeopardize the further technology development. To such bottlenecks is commonly referred to as "valleys of death" in which technologies "die" due to underinvestment. Such valleys of death are particularly likely to occur in the post-lab but pre-market stages. Moving them from the lab to a full scale demonstration project can get very capital intense technologies and public funding which often funds early research gets scarcer at this stage. When this challenge is managed, scaling up for full commercialization becomes the next hurdle – when capital requirements get too high for early stage investors but the technology risk is still unacceptably high for most institutional investors with suitable capacity.

Structure,Content and Contribution of the Thesis

During the course of this Ph.D. thesis, me together with several co-authors conducted research on the interplay between finance and technological change. I develop a guiding framework, where technological change can be explained as the outcome of interactions within and between (i.) the research space where technology is developed by research agents, (ii.) the intermediate technology space which takes the form of a fitness landscape representing potential performance of certain technology configurations, and (iii.) the financial space where financial agents search for possible investment opportunities in technology space.

The present PhD thesis consists of seven chapters. The first introductory chapter elaborates on the theoretical and empirical context, and further suggests a unifying conceptual framework on the network dynamics of research, finance and technological change. I here attempt to explain technological change as the outcome of interaction within and between three dimensions of an higher-level complex system, namely: (i.) the research space where technology is developed by research agents, (ii.) the intermediate technology space which takes the form of a fitness landscape representing potential performance of certain technology configurations, and (iii.) the financial space where financial agents search for possible investment opportunities in technology space. Such conceptual frameworks are helpful in a way that they offer us an intuition of the behavior of systems by reducing their underlying complexity to a readily comprehensible set of elements, their relation, some input and some output delivered as stylized facts. They further help us placing focused empirical and theoretical findings in a broader context.

All of the work in this thesis can be connected to the internal dynamics in one of these dimensions, or the interplay between two. Where needed, chapters aim to establish an empirical or theoretical foundation for further analysis, or focus on analyzing the effects of different variables, illustrating or develop methods to do so. Some of the attempted contributions are empirical, some theoretical, and some are in method development. The empirical context of this work varies broadly, ranging from the cross-industry, equity investment, the smart-grid industry to the singularity movement. Yet, what all of them have in common is that they draw from system and complexity theory, envisioning technological change as the interplay between different subsystems, which are in turn populated by interacting agents or elements. Here, network theory and analysis provides the "glue" connecting these dimensions.

The following six chapters represent research papers written with a variety of co-authors during my PhD. fellowship. The first two lay groundwork by discussing generic issues of research on the finance of innovation and technological change. All following four papers analyze separately a specific and important aspects of network or actor dynamics within or between the proposed three dimensions of technological change, and in combination attempt to enhance our understanding how technology evolves as the macro outcome of micro interactions of actors and entities within and along these dimensions.

In the following, I provide a brief summary of key topics emerged during this Ph.D. projects, and how they are reflected in the work in this thesis.

Measurement of Technological Change

Embracing complexity theory and framing the the evolution of technology as outcome of a complex system has a first direct implication. A characteristic of nonlinear dynamic systems, is the high sensitivity to initial conditions, where small differences can yield to widely diverging outcomes (Kellert, 1994), making even deterministic systems without random behavior hard to predict with traditional methods. Consequently, we are using the right measure, and are able to do so with high precision. Together with my co-author Jesper Lindgaard Christensen, in chapter A I therefore take stock of our existing knowledge foundation that forms the basis for research, decision making and policies regarding investments technological change in the energy sector, which represents the guiding illustration case along this thesis. Our aim is to map what we measure up to now, to which extend of precision we do that, and what we do not measure at all, but could and should. We start with providing an overview of current producers of energy statistics and the data they provide., ranging from primary national data on energy production, consumption and emissions to the state of the art concerning indicators of energy innovation systems and their dynamics. Arguing that investments represents a real-time economic response on changing policy, regulatory frameworks and technological opportunities as well as forward looking measure for future technological change and capacity deployment, we illustrate the benefits gained by a more thorough inclusion of investment data for decision making in industry and policy alike. We particularly emphasize the role of investors as a linkage between public policy and firm level activity, discuss the kind of data needed to sufficiently characterize them and fulfill their particular information need to invest in the renewable energy sector. While doing such a mapping, we further point to several types of flaws and difficulties related to getting a statistical overview of investments in the energy sector, and argue they are not just a matter of increasing the existing statistical efforts and precision but caused by more generic difficulties of the energy sector. We identify four interdependent key challenges for the meaningful utilization of data on investments in the energy system, namely (i.) the delimitation of the sector, (ii.) the identification of firms and (iii.) investors active in it, and (iv.) the measurement of industry dynamics and technological change.

Financing of Innovation

Before exploring further the network dynamics of industrial change, in chapter B my co-author Jesper Lindgaard Christensen and I do groundwork by first investigating some more generic issues of financing the essence of technological change, innovation. In detail, at the Danish context we empirically study what enables firms, one of the main carriers of innovation (Schumpeter, 1942), to access external finance, a critical factor in determining a firm's ability to survive, grow, and engage in innovative activities (Beck and Demirguc-Kunt, 2006). Investments in innovation *per se* appear to embody certain characteristics making them substantially different from other investments. From a financier perspective, investing in radically innovative firms *vis-á-vis* their not or only moderately innovative counterparts, is foremost associated higher information asymmetries between firm and finance, and related with higher risk and uncertainty (Dosi and Orsenigo, 1988) of investment outcomes. This tension is supposed to increase when innovation activities are not based on incremental improvements of existing products, processes or services, but happen in a more radical way, fundamentally diverging from current business-as-usual. In addition, some characteristics associated with the futures innovative and entrepreneurial high growth ventures, such as being young, small are said to cause cause further information asymmetries between financiers and finance seekers, making them likely to experience financial constraints when seeking external capital to fund innovative endeavors Revest et al. (2010). While I later discuss how networks among and between firms and investors might mitigate imperfect and asymmetric information, I here first in isolation analyze the interplay between external finance, firms' quality and quantity of innovation activities, and its structural and outcome characteristics, thereby proposing that not a single but rather certain combinations of characteristics and context makes firms more likely to not find their financial needs met. We indeed find the intensity and type of innovation to matter in a nuanced way. While incremental innovation activities have little effect on the access to external finance, radical innovation activities tend to be penalized by capital markets. This appears to be particularly true for small innovators.

Research network dynamics

This thesis mostly focuses on the effect of networks within the finance sphere or between finance and research/industry, threatening network pattern and dynamics in the research sphere as exogenous. I argue that, for the sake of simplicity, one can at least in the short run assume analytic orthogonality between the dimensions of technological change. Yet, since ample empirical evidence suggests that a firm's strategic positioning in interorganizational networks may affect its innovative performance (e.g. Baum et al., 2000; Powell et al., 1996), and the structure of the overall network affects the innovation output on the aggregated (Fleming et al., 2007a) and firm level (Kudic, 2014; Schilling and Phelps, 2007) alike. Consequently, understanding network dynamics in research helps us discussing the impact finance may play in facilitating the formation of network structure.

In chapter C my co-author Roman Jurowetzki and I investigate the dynamics of heterogeneous firm strategies, resulting network pattern and the rate and direction of technological change in public funded R&D projects in danish smart-grid research. Since this networks are to a large extend constructed by policy and the resulting grant allocation pattern, it provides an interesting setting to discuss how "policy-motivated investors" are able to influence network dynamics in research. We here focus on a theoretical as well as political tension, namely the role of large incumbent firms in such research projects and networks. In innovation system literature and many policy initiatives, engagement of large incumbent actors in the development of emerging technologies, and especially joint research projects together with young SME's, is generally positively perceived as they have the capabilities to fulfill necessary systemic functions in a better way than new start-up firms (Bergek et al., 2013; Bulathsinhala and Knudsen, 2013). Yet, literature on socioeconomic transition and the multi-level perspective (Geels, 2002) provides a more critical perspective, arguing the involvement of incumbents might however alter niche dynamics, making technology outcomes more incremental and adapted to the current unsustainable socio-technical regime. This is particularly evident if the emerging technology is a potential substitution to the existing solutions (Bower and Christensen, 1995). The incumbents' ability to influence the trajectory of technological development can to a large extent be explained by their position in the niche network of early stage research.

A stochastic actor based network analysis suitable to investigate the path dependent evolution of actor driven networks reveals that, in fact, large incumbent companies over time become increasingly dominant in the networks of actors that develop the Danish smart grid. Main force behind this development we find on the supply side of public grant allocation, for instance the preferences of public authorities towards certain firms, technologies, project types. In addition, we identify demand side effects related strategic motives of incumbents to participate in technological niches.

By emphasizing governance and influence related aspects combined with firm characteristics and strategies, we provide an alternative - and perhaps more critical - perspective on research and innovation networks, and the role of the state in their coordination. Methodologically, we demonstrate the richness of stochastic actor-oriented models to answer such questions by modeling collaboration decisions on actor level, and relating them to macro outcomes of structural network evolution.

Investor Networks

While undeniably important, public funding of research and innovation – on which I focus in the beginning of this thesis– has its limits. One is scale, since state budgets only allow to invest so much in any technology. Owing to the increased techno-economic opportunities within knowledge-based economies (Foray and Lundvall, 1996) going hand in hand with the strongly felt uncertainties of scientific and technological innovation (Dosi, 1982, 1988), specialized financial intermediaries dealing with these challenges emerged during the last decades. Venture capitalists (VCs) are a classical - but not the only - example of such intermediaries who combine their unique blend of technological competence and financial skills to provide both financial and managerial support for entrepreneurs in innovative ventures. It has been established by extant research that such specialized "innovation investors" not only promote innovative activities (Kortum and Lerner, 1998, 2000; Samila and Sorenson, 2010, 2011), but they also provide additional value-added support to enable innovative products or services to be rapidly brought to market (Black and Gilson, 1998; Bygrave and Timmons, 1992).

In a connected world where capital as well knowledge is dispersed around the globe, such investments in innovative and entrepreneurial ventures increasingly are made across borders and jurisdictions, in locations with cultural norms, market dynamics and business practices quite distant from the investors local markets. Not surprising, attracting such foreign investments and thereby taping in global pools of capital and knowledge has become an integral goal of recent innovation-related public policies in many developed and emerging economies (Beck et al., 2008; Kortum and Lerner, 2000), yet with widely varying outcomes (Cumming, 2010, 2011). Successful examples who succeeded in the development of a vibrant venture capital industry from scratch are often attributed to network-based strategies, encouraging cooperation between local and foreign investors (Avnimelech et al., 2006; Xiao, 2002).

In chapter D, my co-authors Sofia Johan and Daojuan Wang a way to mitigate information deficits associated with investments over long geographical, institutional and cultural distance by mobilizing knowledge and capabilities of partners within an investor's network of informants (Casamatta and Haritchabalet, 2007; Fiet, 1995). While based on micro-level actions of investors, we mostly focus on macro-level outcomes on country and country-dyad level, in particular we aim to explain the amount of bilateral flows of equity (VC) investments in innovative ventures. We further contrast cross-border venture capital investments in developed and emerging economies, as many emerging economies have been actively supporting their own venture capital markets pursuant to the perceived success of VC contribution to innovation in more developed jurisdictions (Bruton et al., 2004, 2005). These same economies are seeking not only to attract foreign funds but more specifically foreign expertise as it is thought that not only would local entrepreneurs benefit from specialist VC skills, but also that local VCs would benefit from the transfer of knowledge from the more sophisticated foreign VCs. However, underdeveloped investor and property protection, high cultural distance, diverging business ethics and practices, and the perception of corruption in certain jurisdictions are obstacles to the development of these markets.

Incomplete and asymmetric information issues of innovation finance are a – if not the – main guiding topic of my Ph.D. thesis. In this chapter I empirically investigate how investors adjust their strategies to minimize asymmetries, and how these micro-choices manifest in macro-outcomes. Claiming geographical, institutional and cultural distance apparent in most cross-border transactions to be a major obstacle for investments in innovation and technological change, we identify how they can be mitigated by the investors cooperation strategies, and how they differ given the institutional setup of host and target country. We thereby also demonstrate the importance of explicitly taking the institutional context of innovation investments into account, which greatly impacts their quantity as well as quality.

Mapping technological change

Conceptual frameworks, as the one I sketch in this thesis, help us understanding complex systems by identifying overall commonalities, rules, and relationships. However, to make them useful beyond scholarly discussions and support evidence based decision making, such a framework's determinants (elements, relations, input and output) have to be quantifiable. While earlier we provide ample own examples and discuss related work on how to measure elements and their characteristics, their network and interaction pattern within and between finance and research sphere, mapping and measuring elements within the technology sphere represents a more challenging task. In chapter A, we define a set of interrelated challenges for empirical research in the energy sector representative for a large and complex technological system, where the delimitation of sectors and technologies represents the first necessary condition for empirical work. Indeed, the energy area is vast and diverse, including a multitude technologies from different technological fields and deployed in various industries. Many of those technologies can in a specific configuration be used for the production, distribution, storage and efficient consumption of energy, but originate from and are still deployed for the same or different tasks in other sectors. This prevalent technological diversity represents a major challenge for a delimitation of the energy sector and it's subsystems. Yet, such a delineation of technological systems, subsystems, their components and interactions is fundamental for any descriptive or predictive analysis of technological change and its drivers, including finance. This challenge, even though quite distinct, is not unique to the energy sector but nowadays can be found in many large technological systems. Contemporary trends of modularisation and the emergence of "interface technologies" ease the combination and re-combination of components from different technological trajectories, sectors and paradigms, making the line between different sectors increasingly blurry. Among others, the rapid progress of ICT technology led to its penetration of virtually all areas of social and commercial activity, and the development of common data transfer protocols and interfaces is said to make technologies from different trajectory more compatible with each other.

Obviously, static classifications such as industry IPC codes or patent classes are of very limited use to delimit and map such interconnected and rapidly evolving technological systems. Common approaches to do so are mostly limited to qualitative in-depth case studies (Davies, 1996), quantitative methods based on patents (Verspagen, 2007) or scientific publication (Wagner and Leydesdorff, 2005) data, and more generic simulation models (Dawid, 2006; Lopolito et al., 2013). While undeniably useful, they either require massive effort to qualitatively analyze complex interaction patterns in technological space, or rely on quantitative data only available with non-negligible time delay, and only relevant for certain technology domains, often underestimating the context in which technology is used.

During the last decade we have witnessed tremendous growth of freely available digital information, often in the form of unstructured text data from sources such as web-sites and blogs, written communication of communities in forums or via e-mail, and knowledge repositories (e.g. SSRN, Researchgate). The topicality and sheer amount of such data bear great opportunities for social science research in general, and particularly to timely analyze complex technological change. Most recently, social scientists have also started to deploy methods from the fields of computational linguistic and natural language processing (NLP) to advance empirical research on the development of science and technology (DiMaggio et al., 2013; McFarland et al., 2013; Mohr and Bogdanov, 2013; Ramage et al., 2009). In their essence, such linguistically informed methods are capable of identifying patterns of language usage in large bodies of text and communication. Taping in this new source and utilizing newest advances in NLP and network analysis, my co-author Roman Jurowetzki and I in chapter E develop a framework and suggest a set of methods geared towards mapping technological change in complex interdependent systems by using large amounts of unstructured text data from various on- and offline sources. Such an approach integrates the broad multidimensional perspective of qualitative researchers with quantitative objectivity given by the machine learning based methodology. As empirical example we use the broad area of *Technological Singularity*, a umbrella term for different technologies ranging from neuroscience to machine learning and bioengineering which are seen as main contributors to the development of artificial intelligence and human enhancement technologies. We extract a large number of text documents all over the internet, using a social search routine that we built around the followship structure within the microblogging service twitter. Using entity recognition tools from the semantic web area, we reduce documents to technology-term representations and finally generate a semantic timestep network of technology fragments. We then use community detection techniques to identify fields of densely related technologies. By doing so, we are able to observe the evolution of such fields over time, and identify the technological trajectories they follow. We believe this to be a crucial step towards a dynamic and adaptable real-time mapping of technological evolution. We further suggest feasible methods such as entity identification techniques to link these technologies again to actors in the research and finance sphere. Having such tools at hand, in further steps a more nuanced discourse on the interplay of finance and technology beyond the aggregation of investments fitting in certain static classifications is possible. Instead, a dynamic mapping of technological change as the reconfiguration of relationships of technologies enables us to analyze the impact of investments in terms of its contribution to the technological system's evolution in a certain direction.

Simulation

After the theoretical as well as empirical groundwork, in chapter F my coauthor Elena Mas Tur and I make a first attempt towards more predictive models by developing a mathematical formalization of the interaction between finance, research and technological change. While we exhaustively discuss possibilities to model interactions within and between all three considered dimensions (research, technology and investment space), or main focus lies on the effect of finance on technological change - the guiding topic of this PhD thesis. We carefully elaborate on the endogeneity between characteristics of all three dimensions, yet demonstrate that - for the sake of analytic orthogonality - they can be studied in isolation, at least in the short run. In detail, we develop a model of investment by heterogeneous and interacting financial agents in research projects on a given landscape of technological opportunities. Investment decisions are explained by the topology of the technology landscape, the agents' capability to receive and interpret incomplete landscape information, and their investment capacity. We are particularly interested in the effects of different information-sharing an co-investment network structures among financial agents on the rate and direction of technological change. We model financial agents to observe emerging technologies on a technology "fitness landscape", and select potential investment targets according to their perceived risk-adjusted returns, where risks are a function of the technology's maturity and the returns of the achieved technological fitness. Subject to imperfect information and bounded rationality, financial agents are heterogeneous in their view of the landscape determining the potential investment targets they are able to spot as well as in their forecasting ability determining the accuracy of their prediction of achievable technological fitness. Assuming a trade-off between search radius and forecasting ability, the population of financial agents will consist of more specialized investors with a narrow view on the landscape but high forecasting ability within this area, and more generalized ones who can search a large area but have a low forecasting ability. We observe which configuration of financial agents lead to high rates of technological change and diversity, and in which technologies get stuck in the "valley of death". In a next step, we introduce investor networks and allow financial agents to co-invest together with their connected peers in order to pool financial resources and get access to their forecasting capability in a specific technological domain. While we expect such networks *per se* to be conductive, we are interested which network structures and compositions lead to the high rates of technological change and diversity.

Combined Contribution - A Framework of Finance and Technological Change

After surveying relevant literature and concepts and elaborating on them in separation, this chapter aims to integrate the insights gained in a "guiding" conceptual framework for the research to come. Such conceptual frameworks are helpful in a way that they offer us an intuition of the behavior of systems by reducing their underlying complexity to a readily comprehensible set of elements, their relation, some input and some output delivered as stylized facts. They further help us to place focused empirical and theoretical findings in a broader context.

In a nutshell, this thesis attempts to enhance our understanding of the role of finance in facilitating technological change and socioeconomic transitions. Invention and innovation – which are the creation and commercialization of novel products, services, processes, and business models – lay at the very core of such transitions. In a neo-schumpeterian tradition, I emphasize the duality of invention and finance as driving forces of technological change in modern capitalistic economies. A well-established key insight from a long tradition of innovation studies is that it is not happening in isolation but rather as a result of a collaborate effort between heterogeneous actors. Main arguments put forward in this thesis is that this claim can also be expanded to the financing thereof. Indeed, literature is full of hints as to how relationships between firms and investors influence their access to external finance, and how relationships among investors enable them to carry out investments they would not be able to undergo on their own. Arguably, the impact of such relationships can be expected to matter even more for investments in innovation and technological change, where trust and knowledge transfer as an outcome potentially mitigate uncertainty and incomplete information issues associated with such investments.[9]

Literature on innovation systems demonstrates that for reasons of clarity and comprehensibility it can be helpful to depict the interaction of complex socio-techno-economic systems as the interaction between subsystems on different levels of aggregation, with innovation and technological change as an outcome. Following this stream of thought, I attempt to explain technological change as the outcome of interaction within and between three dimensions of an higher-level complex system, namely: (i.) the research space where technology is developed by research agents, (ii.) the intermediate technology space which takes the form of a fitness landscape representing potential performance of certain technology configurations, and (iii.) the financial space where financial agents search for possible investment opportunities in technology space. Figure F.1 provides an illustration thereof, and chapter F provides a more exhaustive discussion regarding the dimensions and their interplay.

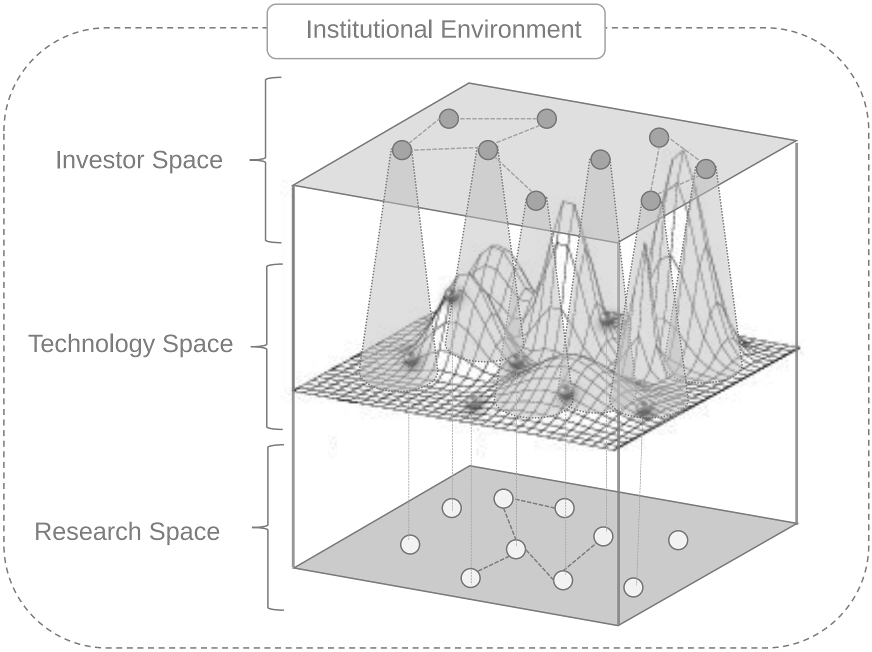
This comes close to common conceptualization within the literature on national innovation systems, where the innovation capability of a nation state is explained as the pattern, degree and quality of interaction between national subsystems such as the financial or educational one and the institutional framework. Yet, I make two crucial distinctions. First, the dimensions of the guiding framework in this thesis are delineated by the agents populating them and their behavior, which gears it towards micro-level analyses of interaction between heterogeneous agents. Second, I explicitly avoid a delineation by regional or national boarders. While I agree that many important decisions influencing long-run technological change – such as legal frameworks and education policies – are made on a national level, financial institutions, investors, and investment patterns have become increasingly detached from the nation state and become globally oriented during the last decades.[10]

Yet, for the resulting framework to be of use for statistical analysis and mathematical modeling – as I do during the course of this thesis – one has to find a balance between how much of reality it captures and how understandable the mechanisms are to derive useful implications. In this framework, I

[9] Yet, even though in this thesis I emphasize the enabling role of relationships and networks in the innovation process, I also highlight in later chapters lock-ins and other "status quo" maintaining forces less conductive for innovation and technological change.

[10] Nevertheless, even though not used for delineation purposes, the role of space and geography can still to be found in this framework, mainly as characteristics of links between the actors.

Fig. 2: Illustration of the theoretical framework



explicitly take co-evolutionary forces and the resulting endogeneity caused by multiple feedback loops between the three dimensions into account. Yet, I also argue during the course of this thesis that for short- and medium-run analysis, it is possible to study dynamics within these dimensions independently – taking inputs from other dimensions as given. Furthermore, for the sake of clarity, I focus on the interaction of the elements within and between research, technology, and financial space, thereby taking the institutional context as given. This is surely a crude simplification of technological change which always happens in a social, cultural and institutional context (Bijker, 1997; Bijker et al., 1987; Hughes, 1987). Indeed, all the really complicated things, such as the collective formation of value and meaning, cultural norms, attitudes, policy, regulation and so forth, I collect under the umbrella term "institutions" and assume them to be exogenous. They represent a main part of the systems initial conditions as well as its mechanisms. They determine the selection criteria and thereby population dynamics of the system's entities as well as the criteria how this entities create links, and how these links influence them. In reality culture, society, and institutions are also shaped by technology, research, and finance. Still, integrating such a multiplicity of additional mechanisms in a comprehensive yet understandable framework appears to be too much of a challenge. In favor of this choice speaks that most of the things we economists like to label institutions can be assumed to be somewhat stable over time and only change slowly and gradually.

The overall implication and insights to be gained from this thesis and its provided framework are geared towards facilitating the development of a sustainable energy system. Indeed, the interdisciplinarity of knowledge needed and resulting actor heterogeneity, the system character and complexity, and high capital intensity of the energy sector call for new theoretical and analytical approaches. However, even though the conditions appear to be unique in their combination, they stem from more generic problems, which can be observed in several other sectors. Examples are the enormous capital intensity of the R&D process and the long amortization time in pharmaceuticals, the reliance on infrastructure and state regulation in telecommunication, and the technical complexity of aerospace. Consequently I believe, the resulting framework of this PhD thesis has, *mutatis mutandis*, the potential to be deployed in a variety of other technological systems.

I provide evidence how network structures among investors – and with innovators – greatly influence the rate and direction of technological change, and how this influence varies with respect to different characteristics of technological systems. I thereby identify how investors via interaction and cooperation alleviate barriers associated with investments in innovation in complex technological systems – such as uncertainty, asymmetric and imperfect information, and bounded rationality. Further, I also demonstrate how targeted investments in technological change are able to influence the network structure among firms and researchers active in the innovation process. I thereby provide direct policy implications on how to facilitate the emergence of network structures among innovators and investors which are conducive for a certain desired rate and direction of technological change. Further, this thesis aims for an academic contribution by conceptualizing technological change in a Schumpeterian duality of micro-level interaction between investors and innovators, and demonstrating methods to conduct research on this interaction.

I hope the findings of this thesis stimulate further research, and the developed framework provides useful guidance to do so. Indeed, much is still o be done. Methodologically, for instance, to further advance the explanatory power of a framework consisting of multiple dimensions of interconnected and interacting networks, the implementation modern advances in the analysis of multilayer networks[11] appear s to be a particularly fruitful avenue of research. Such multilayer network analysis aims to understand how different types of nodes in different dimensions, and connected by different types of edges interact with – and relate to – each other. Indeed, networks within and between investors and innovators appear to co-evolve with the technological system they are embedded in. To conclude, much is still to be done to understand this co-evolution, calling for new sources of data, new methods, and new theory alike. I hope this thesis provides a fruitful first attempt towards a more eclectic understanding of technological change as the outcome of micro-level interaction between investors, innovators, and technology.

[11] For an extraordinary exhaustive review consider Kivelä et al. (2013).

References

Acs, Z. J., Arenius, P., Hay, M., and Minniti, M. (2004). Global entrepreneurship monitor. *Executive Report, London Business School, Babson*.

Ahuja, G., Soda, G., and Zaheer, A. (2007). Call for papers: The genesis and dynamics of networks. *Organization Science*, 18(6):1024.

Akerlof, G. A. (1970). The market for lemons: Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3):488–500.

Antunes Nogueira, L., Hain, D. S., and Lindgard Christensen, J. (2015). Greenagers out in town - the collaboration patterns of entrepreneurial, green firms. working paper, presented at SBE "Green Startups" special issue conference, May 2015, Winchester, UK.

Arrow, K. J. (1962). Economic welfare and the allocation of resources for invention. In Nelson, R., editor, *The Rate and Direction of Inventive Activity*, pages 609–625. Princeton University Press.

Astolfi, P., Baron, S., and Small, M. J. (2008). Financing renewable energy. *Commercial lending Review*, 23(2):3–8.

Audretsch, D. (1995). *Innovation and industry evolution*. The MIT Press.

Audretsch, D. (2006). *Entrepreneurship, innovation and economic growth*. Edward Elgar Publishing.

Avnimelech, G., Kenney, M., and Teubal, M. (2006). Creating venture capital industries that co-evolve with high tech: Insights from an extended industry life cycle perspective of the Israeli experience. *Research Policy*, 35(10):1477–1498.

Barabâsi, A., Jeong, H., Néda, Z., Ravasz, E., Schubert, A., and Vicsek, T. (2002). Evolution of the social network of scientific collaborations. *Physica A: Statistical Mechanics and its Applications*, 311(3):590–614.

Battiston, S., Caldarelli, G., Georg, C.-P., May, R., and Stiglitz, J. (2013). Complex derivatives. *Nature Physics*, 9(3):123–125.

Baum, J., Calabrese, T., and Silverman, B. S. (2000). Don't go it alone: Alliance network composition and startups' performance in canadian biotechnology. *Strategic Management Journal*, 21(3):267–294.

Beck, T. and Demirguc-Kunt, A. (2006). Small and medium-size enterprises: Access to finance as a growth constraint. *Journal of Banking & Finance*, 30(11):2931–2943.

Beck, T., Feyen, E., Ize, A., and Moizeszowicz, F. (2008). Benchmarking financial development. *World Bank Policy Research Working Paper 4638*.

Bergek, A., Berggren, C., Magnusson, T., and Hobday, M. (2013). Technological discontinuities and the challenge for incumbent firms: Destruction, disruption or creative accumulation? *Research Policy*.

Bijker, W. E. (1997). *Of bicycles, bakelites, and bulbs: Toward a theory of sociotechnical change*. MIT press.

Bijker, W. E., Hughes, T. P., and Pinch, T. J. (1987). *The Social Construction of Technological Systems: New Directions in the Sociology and History of Technology*. MIT Press.

Black, B. and Gilson, R. (1998). Venture capital and the structure of capital markets: banks versus stock markets. *Journal of Financial Economics*, 47(3):243–277.

Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., and Hwang, D.-U. (2006). Complex networks: Structure and dynamics. *Physics reports*, 424(4):175–308.

Bonaccorsi, A. and Thoma, G. (2007). Institutional complementarity and inventive performance in nano science and technology. *Research Policy*, 36(6):813–831.

Bower, J. L. and Christensen, C. M. (1995). *Disruptive technologies: catching the wave*. Harvard Business Review Video.

Brealey, R., Leland, H. E., and Pyle, D. H. (1977). Informational asymmetries, financial structure, and financial intermediation. *The Journal of Finance*, 32(2):371–387.

Breschi, S. and Catalini, C. (2010). Tracing the links between science and technology: An exploratory analysis of scientists and inventors networks. *Research Policy*, 39(1):14–26.

Bruton, G., Ahlstrom, D., and Yeh, K. S. (2004). Understanding venture capital in east Asia: the impact of institutions on the industry today and tomorrow. *Journal of World Business*, 39(1):72–88.

Bruton, G. D., Fried, V. H., and Manigart, S. (2005). Institutional influences on the worldwide expansion of venture capital. *Entrepreneurship Theory and Practice*, 29(6):737–760.

Bulathsinhala, N. A. and Knudsen, M. P. (2013). The role of organizational knowledge integrators in large r&d projects. Conference proceeding, 35th DRUID Celebration Conference, ESADE Business School, Barcelona, Spain.

Burer, M. J. and Wustenhagen, R. (2009). Which renewable energy policy is a venture capitalist's best friend? empirical evidence from a survey of international cleantech investors. *Energy Policy*, 37(12):4997–5006.

Burt, R. S. (1992). Structural holes: The social structure of competition. In Nohria, N. and Eccles, R., editors, *Networks and Organizations*, pages 57–91.

Burt, R. S. (2000). Decay functions. *Social networks*, 22(1):1–28.

Bygrave, W. D. (1987). Syndicated investments by venture capital firms: A networking perspective. *Journal of Business Venturing*, 2(2):139–154.

Bygrave, W. D. and Timmons, J. A. (1992). *Venture capital at the crossroads*. Harvard Business Press.

Canepa, A. and Stoneman, P. (2008). Financial constraints to innovation in the uk: evidence from cis2 and cis3. *Oxford Economic Papers*, 60(4):711–730.

Cantner, U. and Graf, H. (2011). Innovation networks: formation, performance and dynamics. In Antonelli, C., editor, *Handbook on the economic complexity of technological change*, pages 366–394. Edward Elgar Publishing.

Carlsson, B. and Stankiewicz, R. (1991). In search of useful public policies: key lessons and issues for policy makers. *Journal of evolutionary economics*, 1(2):93–118.

Carreira, C. and Silva, F. (2010). No deep packets: Some stylized empirical results on firms? *Journal of Economic Surveys*, 24(4):731–753.

Casamatta, C. and Haritchabalet, C. (2007). Experience, screening and syndication in venture capital investments. *Journal of Financial Intermediation*, 16(3):368–398.

Chen, S.-H., Huang, M.-H., and Chen, D.-Z. (2012a). Identifying and visualizing technology evolution: a case study of smart grid technology. *Technological Forecasting and Social Change*, 79(6):1099–1110.

Chen, S.-H., Huang, M.-H., and Chen, D.-Z. (2012b). Technological forecasting & social change. *Technological Forecasting & Social Change*, 79(6):1099–1110.

Cumming, D. J. (2010). *Venture Capital: Investment Strategies, Structures, and Policies*, volume 9. Wiley.

Cumming, D. J. (2011). Review essay: Public policy and the creation of active venture capital markets. *Venture Capital: An International Journal of Entrepreneurial Finance*, 13(1):75–94.

David, P., Hall, B., and Toole, A. (2000). Is public r&d a complement or substitute for private r&d? a review of the econometric evidence. *Research Policy*, 29(4):497–529.

Davies, A. (1996). Innovation in large technical systems: the case of telecommunications. *Industrial and Corporate Change*, 5(4):1143–1180.

Dawid, H. (2006). *Agent-based models of innovation and technological change*, volume 2, chapter 25, pages 1235–1272. Elsevier.

Dierickx, I. and Cool, K. (1989). Asset stock accumulation and sustainability of competitive advantage. *Management Science*, 35(12):1504–1511.

DiMaggio, P., Nag, M., and Blei, D. (2013). Exploiting affinities between topic modeling and the sociological perspective on culture: Application to newspaper coverage of us government arts funding. *Poetics*, 41(6):570–606.

Doreian, P. and Stokman, F. N. (2005). The dynamics and evolution of social networks. In P. Doreian, . F. N. S., editor, *Evolution of Social Networks*, volume 2nd edition, pages 1–17, New York. Gordon & Breach.

Dosi, G. (1982). Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. *Research policy*, 11(3):147–162.

Dosi, G. (1988). Sources, procedures, and microeconomic effects of innovation. *Journal of economic literature*, pages 1120–1171.

Dosi, G. (1990). Finance, innovation and industrial change. *Journal of Economic Behavior & Organization*, 13(3):299–319.

Dosi, G. and Orsenigo, L. (1988). Coordination and transformation: an overview of structures, behaviours and change in evolutionary environments. In Dosi, G., Freeman, C., Nelson, R., and Soete, L., editors, *Technical Change and Economic Theory*, pages 13–37, London. Pinter Publishers.

Ebbers, J. and Wijnberg, N. (2010). Disentangling the effects of reputation and network position on the evolution of alliance networks. *Strategic Organization*, 8(3):255–275.

Fiet, J. O. (1995). Reliance upon informants in the venture capital industry. *Journal of Business Venturing*, 10(3):195–223.

Fischer, M., Ingold, K., Sciarini, P., and Varone, F. (2012). Impacts of market liberalization on regulatory network: A longitudinal analysis of the swiss telecommunications sector. *Policy Studies Journal*, 40(3):435–457.

Fleming, L. and Frenken, K. (2007). The evolution of inventor networks in the silicon valley and boston regions. *Advances in Complex Systems*, 10(01):53–71.

Fleming, L., King, C., and Juda, A. (2007a). Small worlds and regional innovation. *Organization Science*, 18(6):938–954.

Fleming, L., Mingo, S., and Chen, D. (2007b). Collaborative brokerage, generative creativity, and creative success. *Administrative Science Quarterly*, 52(3):443–475.

Fleming, L. and Sorenson, O. (2001). Technology as a complex adaptive system: evidence from patent data. *Research Policy*, 30(7):1019–1039.

Fontana, R., Nuvolari, A., and Verspagen, B. (2009). Mapping technological trajectories as patent citation networks. an application to data communication standards. *Economics of Innovation and New Technology*, 18(4):311–336.

Foray, D. and Lundvall, B. (1996). The knowledge-based economy: from the economics of knowledge to the learning economy. *Employment and Growth in the Knowledge-based Economy*, pages 11–32.

Freeman, C. (1974). *The Economics of Industrial Innovation*. Penguin, Harmondsworth.

Freeman, C. (1987). *Technology Policy and Economic Performance: Lessons from Japan*. Pinter Publishers, London.

Garlaschelli, D. and Loffredo, M. I. (2005). Structure and evolution of the world trade network. *Physica A: Statistical Mechanics and its Applications*, 355(1):138–144.

Geels, F. (2002). Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and a case-study. *Research policy*, 31(8):1257–1274.

Giuliani, E. (2007). The selective nature of knowledge networks in clusters: evidence from the wine industry. *Journal of Economic Geography*, 7(2):139–168.

Glückler, J. (2007). Economic geography and the evolution of networks. *Journal of Economic Geography*, 7(5):619–634.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, 78(6):1360–1380.

Grant, R. and Baden-Fuller, C. (2004). A knowledge accessing theory of strategic alliances. *Journal of Management Studies*, 41(1):61–84.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, 17:109–122.

Grubb, M. (2004). Technology innovation and climate change policy: an overview of issues and options. *Keio economic studies*, 41(2):103.

Gulati, R. (1995). Social structure and alliance formation patterns: A longitudinal analysis. *Administrative science quarterly*, pages 619–652.

Gulati, R. (1999). Network location and learning: The influence of network resources and firm capabilities on alliance formation. *Strategic management journal*, 20(5):397–420.

Hagedoorn, J. (1990). Organizational modes of inter-firm co-operation and technology transfer. *Technovation*, 10(1):17–30.

Hall, B. H. (2010). The financing of innovative firms. *Review of Economics and Institutions*, 1(1):1–30.

Hall, B. H. and Lerner, J. (2009). The financing of r&d and innovation. NBER Working Paper 15325.

Hall, D., Jurafsky, D., and Manning, C. D. (2008). Studying the history of ideas using topic models. In *Proceedings of the conference on empirical methods in natural language processing*, pages 363–371. Association for Computational Linguistics.

Hanusch, H. and Pyka, A. (2007). Principles of neo-schumpeterian economics. *Cambridge Journal of Economics*, 31(2):275–289.

Hausmann, R. and Hidalgo, C. A. (2011). The network structure of economic output. *Journal of Economic Growth*, 16(4):309–342.

Hidalgo, C., Klinger, B., Barabási, A., and Hausmann, R. (2007). The product space conditions the development of nations. *Science*, 317(5837):482–487.

Hidalgo, C. A. and Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, 106(26):10570–10575.

Hochberg, Y. V., Ljungqvist, A., and Lu, Y. (2007). Whom you know matters: Venture capital networks and investment performance. *The Journal of Finance*, 62(1):251–301.

Hughes, T. P. (1987). *The Evolution of Large Technological Systems*, pages 51–82. The MIT Press.

IPCC (2007). *Climate Change 2007: Mitigation of Climate Change*. Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge.

Jaeger, C. C., Paroussos, L., Mangalagiu, D., Kupers, R., Mandel, A., and Tabara, J. D. (2011). A new growth path for europe. *Generating Prosperity and Jobs in the Low-Carbon Economy. Synthesis Report*, 1.

Jaffe, A. (2008). The science of science policy: reflections on the important questions and the challenges they present. *The Journal of Technology Transfer*, 33(2):131–139.

Jurowetzki, R. and Hain, D. S. (2014). Mapping the (r-) evolution of technological fields – a semantic network approach. In Aiello, L. M. and McFarland, D., editors, *Social Informatics*, volume 8851 of *Lecture Notes in Computer Science*, pages 359–383. Springer International Publishing.

Kaplan, S. and Tripsas, M. (2008). Thinking about technology: Applying a cognitive lens to technical change. *Research Policy*, 37(5):790–805.

Kauffman, S. A. (1993). *The origins of order: Self-organization and selection in evolution*. Oxford university press.

Kellert, S. H. (1994). *In the wake of chaos: Unpredictable order in dynamical systems*. University of Chicago press.

Kenney, M. (2011). Venture capital investment in the greentech industries: a provocative essay. In Wüstenhagen, R. and Wuebker, R., editors, *Handbook of Research on Energy Entrepreneurship*, page 214. Cheltenham, UK: Edward Elgar Publishing.

Kilduff, Martin; Tsai, W. (2003). *Social networks and organizations*. SAGE Publications Limited.

Kivelä, M., Arenas, A., Barthelemy, M., Gleeson, J. P., Moreno, Y., and Porter, M. A. (2013). Multilayer networks. *arXiv preprint arXiv:1309.7233*.

Klette, T., Møen, J., and Griliches, Z. (2000). Do subsidies to commercial r&d reduce market failures? microeconometric evaluation studies. *Research Policy*, 29(4):471–495.

Knight, F. H. (1921). *Risk, Uncertainty and Profit*. University of Chicago Press.

Kogut, B. and Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization science*, pages 383–397.

Kortum, S. and Lerner, J. (1998). Does venture capital spur innovation? NBER Working Paper 6846: Available at: http://www.nber.org/papers/w6846.

Kortum, S. and Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *RAND Journal of Economics*, pages 674–692.

Kronegger, L., Mali, F., Ferligoj, A., and Doreian, P. (2012). Collaboration structures in Slovenian scientific communities. *Scientometrics*, 90(2):631–647.

Kudic, M. (2014). *Innovation Networks in the German Laser Industry: Evolutionary Change, Strategic Positioning, and Firm Innovativeness*. Springer.

Kuhn, T. S. (1962). *The Structure of Scientific Revolutions*. University of Chicago Press.

Lavie, D. (2006). The competitive advantage of interconnected firms: An extension of the resource-based view. *The Academy of Management Review*, 31(3):638–658.

Levinthal, D. A. (1997). Adaptation on rugged landscapes. *Management science*, 43(7):934–950.

Lewis, J. and Wiser, R. (2007). Fostering a renewable energy technology industry: An international comparison of wind industry policy support mechanisms. *Energy Policy*, 35(3):1844–1857.

Lopolito, A., Morone, P., and Taylor, R. (2013). Emerging innovation niches: An agent based model. *Research Policy*, 42(6):1225–1238.

Lund, H. and Mathiesen, B. (2009). Energy system analysis of 100% renewable energy systems – the case of denmark in years 2030 and 2050. *Energy*, 34(5):524–531.

Lundvall, B.-Å. (1992). *National Systems of Innovation: Toward a theory of innovation and interactive learning*. London: Pinter Publishers.

Manolova, T. S., Manev, I. M., and Gyoshev, B. S. (2013). Friends with money? owner?s financial network and new venture internationalization in a transition economy. *International Small Business Journal*.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization science*, 2(1):71–87.

Markose, S. M. (2013). Systemic risk analytics: A data-driven multi-agent financial network (mafn) approach. *Journal of Banking Regulation*, 14(3):285–305.

Mazzucato, M. (2011). The entrepreneurial state.

McFadden, D. (2001). Economic choices. *American Economic Review*, pages 351–378.

McFarland, D. A., Ramage, D., Chuang, J., Heer, J., Manning, C. D., and Jurafsky, D. (2013). Differentiating language usage through topic models. *Poetics*, 41(6):607–625.

Melin, G. and Persson, O. (1996). Studying research collaboration using co-authorships. *Scientometrics*, 36(3):363–377.

Merton, R. K. (1957). The role-set: Problems in sociological theory. *British journal of Sociology*, pages 106–120.

Mogoutov, A., Cambrosio, A., Keating, P., and Mustar, P. (2008). Biomedical innovation at the laboratory, clinical and commercial interface: A new method for mapping research projects, publications and patents in the field of microarrays. *Journal of Informetrics*, 2(4):341–353.

Mohr, J. W. and Bogdanov, P. (2013). Introduction - topic models: What they are and why they matter. *Poetics*, 41(6):545–569.

Murray, F. (2002). Innovation as co-evolution of scientific and technological networks: exploring tissue engineering. *Research Policy*, 31(8):1389–1403.

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2):187–221.

Mytelka, L. and Delapierre, M. (1987). The alliance strategies of European firms in the information technology industry and the role of ESPRIT. *JCMS: Journal of Common Market Studies*, 26(2):231–253.

Nallapati, R., Shi, X., McFarland, D. A., Leskovec, J., and Jurafsky, D. (2011). Leadlag LDA: Estimating topic specific leads and lags of information outlets. In *ICWSM*.

Nelson, R. R. (1959). The simple economics of basic scientific research. *The Journal of Political Economy*, 67(3):297–306.

Nelson, R. R. (1993). *National innovation systems: a comparative analysis*. Oxford University Press, USA.

Newman, M. (2004). Who is the best connected scientist? a study of scientific coauthorship networks. *Complex networks*, pages 337–370.

Newman, M., Barabási, A.-L., and Watts, D. J. (2006). *The structure and dynamics of networks*. Princeton University Press.

Pavitt, K. (1982). R&d, patenting and innovative activities: a statistical exploration. *Research Policy*, 11(1):33–51.

Pavitt, K. (1998). The inevitable limits of eu r&d funding. *Research Policy*, 27(6):559–568.

Perez, C. (2002). *Technological revolutions and financial capital: The dynamics of bubbles and golden ages*. Edward Elgar Publishing.

Perez, C. (2004). Finance and technical change: A neo-schumpeterian perspective. In Hanusch, H. and Pyka, A., editors, *The Elgar Companion to Neo-Schumpeterian Economics*. Edward Elgar, Cheltenham.

Perez, C. (2010). Technological revolutions and techno-economic paradigms. *Cambridge Journal of Economics*, 34:185–202.

Perez, C. (2011). The financial crisis and the future of innovation: A view of technical change with the aid of history. In van Tilburg et al., editor, *Let finance follow and flow: Essays on finance and innovation*. The Hague: AWT.

Popp, D., Newell, R., and Jaffe, A. (2009). Energy, the environment, and technological change. In Hall, B. H. and Rosenberg, N., editors, *Handbook of the Economics of Innovation*, volume 2. North-Holland.

Powell, W., Koput, K., and Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative science quarterly*, pages 116–145.

Powell, W. W., White, D. R., Koput, K. W., and Owen-Smith, J. (2005). Network dynamics and field evolution: The growth of interorganizational collaboration in the life sciences1. *American journal of sociology*, 110(4):1132–1205.

Pyka, A. (2002). Innovation networks in economics: from the incentive-based to the knowledge-based approaches. *European Journal of Innovation Management*, 5(3):152–163.

Rajan, R. and Zingales, L. (1996). Financial dependence and growth. Technical report, National Bureau of Economic Research.

Ramage, D., Manning, C. D., and McFarland, D. A. (2010). Which universities lead and lag? toward university rankings based on scholarly output. In *Proc. of NIPS Workshop on Computational Social Science and the Wisdom of the Crowds*. Citeseer.

Ramage, D., Rosen, E., Chuang, J., Manning, C. D., and McFarland, D. A. (2009). Topic modeling for the social sciences. In *NIPS 2009 Workshop on Applications for Topic Models: Text and Beyond*, volume 5.

Renneboog, L., Ter Horst, J., and Zhang, C. (2008). Socially responsible investments: Institutional aspects, performance, and investor behavior. *Journal of Banking & Finance*, 32(9):1723–1742.

Revest, V., Sapio, A., et al. (2010). Financing technology-based small firms in Europe: what do we know? *Small Business Economics*, pages 1–27.

Roukny, T., Bersini, H., Pirotte, H., Caldarelli, G., and Battiston, S. (2013). Default cascades in complex networks: Topology and systemic risk. *Scientific reports*, 3.

Rowley, T., Behrens, D., and Krackhardt, D. (2000). Redundant governance structures: an analysis of structural and relational embeddedness in the steel and semiconductor industries. *Strategic Management Journal*, 21(3):369–386.

Salerno, M., Landoni, P., and Verganti, R. (2010). Funded research projects as a tool for the analysis of emerging fields: the case of nanotechnology. Paper presented at the SPRU 40th anniversary conference – the future of science, technology and innovation policy.

Samila, S. and Sorenson, O. (2010). Venture capital as a catalyst to commercialization. *Research Policy*, 39:1348–1360.

Samila, S. and Sorenson, O. (2011). Venture capital, entrepreneurship, and economic growth. *The Review of Economics and Statistics*, 93(1):338–349.

Saxenian, A. (2001). Beyond boundaries: Open labor markets and learning in silicon valley. In Arthur, M. and Rousseau, D., editors, *The Boundaryless Career: A new Employment Principle for a new Organizational Era*, pages 23–39. New York: Oxford University Press.

Schilling, M. and Phelps, C. (2007). Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Science*, 53(7):1113–1126.

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*, volume 55. Harvard University Press: Cambridge, Mass. (originally published in German in 1911; reprinted by Transaction Publishers, New Brunswick, New Jersey in 1997).

Schumpeter, J. A. (1942). *Capitalism, Socialism and Democracy*. Harper, New York.

Serrano, M. A. and Boguñá, M. (2003). Topology of the world trade web. *Physical Review E*, 68(1):015101.

Sharp, M. (1991). The single market and European technology policies. In Freeman, C., Sharp, M., and Walker, W., editors, *Technology and the Future of Europe: Global Competition and the Environment in the 1990s*. London: Pinter.

Simmel, G. (1955). The web of group affiliations. *Conflict and the web of group affiliations*, pages 125–95.

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1):pp.99–118.

Simon, H. A. (1969). *The sciences of the artificial*, volume 136. MIT press.

Simon, H. A. (1991). *The architecture of complexity*. Springer.

Singh, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management science*, 51(5):756–770.

Spender, J.-C. and Grant, R. M. (1996). Knowledge and the firm: overview. *Strategic management journal*, 17(S2):5–9.

Stiglitz, J. and Weiss, A. (1981). Credit rationing in markets with incomplete information. *American Economic Review*, 71(3):393–410.

Strogatz, S. H. (2001). Exploring complex networks. *Nature*, 410(6825):268–276.

Stuart, T. E. (2000). Interorganizational alliances and the performance of firms: A study of growth and innovation rates in a high-technology industry. *Strategic management journal*, 21(8):791–811.

Teece, D. J., Pisano, G., and Shuen, A. (1997). Dynamic capabilities and strategic management: organizing for innovation and growth. *Strategic Management Journal*, 18(7):509–533.

Tsoutsos, T. and Stamboulis, Y. (2005). The sustainable diffusion of renewable energy technologies as an example of an innovation-focused policy. *Technovation*, 25(7):753–761.

Tversky, A. and Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *science*, 185(4157):1124–1131.

Tylecote, A. (2007). The role of finance and corporate governance in national systems of innovation. *Organization Studies*, 28(10):1461–1481.

Uzzi, B. (1999). Embeddedness in the making of financial capital: How social relations and networks benefit firms seeking financing. *American sociological review*, pages 481–505.

Uzzi, B. and Gillespie, J. J. (2002). Knowledge spillover in corporate financing networks: Embeddedness and the firm's debt performance. *Strategic Management Journal*, 23(7):595–618.

Van de Bunt, G. and Groenewegen, P. (2007). An actor-oriented dynamic network approach the case of interorganizational network evolution. *Organizational Research Methods*, 10(3):463–482.

Van Rijnsoever, F., Welle, L., and Bakker, S. (2012). Credibility and legitimacy in policy-driven innovation networks: Resource dependencies and expectations in dutch electric vehicle subsidies.

Verspagen, B. (2007). Mapping technological trajectories as patent citation networks: A study on the history of fuel cell research. *Advances in Complex Systems*, 10(01):93–115.

Wagner, C. and Leydesdorff, L. (2005). Network structure, self-organization, and the growth of international collaboration in science. *Research policy*, 34(10):1608–1618.

Winter, S. (1984). Schumpeterian competition in alternative technological regimes. *Journal of Economic Behavior & Organization*, 5(3-4):287–320.

Xiao, W. (2002). The new economy and venture capital in china. *Perspectives*, 3(6):30.

Zucker, L. G., Darby, M. R., Brewer, M. B., and Peng, Y. (1995). Collaboration structure and information dilemmas in biotechnology: Organizational boundaries as trust production. ISSR Working Papers in the Social Sciences.

Part II

Papers

Paper A

Knowing where to go: The Knowledge Foundation for Investments in Energy Innovation

Jesper Lindgaard Christensen[†] and Daniel S. Hain[†]
[†] *IKE, Department of Business and Management, Aalborg University, DK*

The layout has been revised, and a preface not included in the original article has been added.

Abstract

Possibilities for reducing carbon-dioxin emissions rest to a large extent on new solutions and consumption, which in turn requires innovation. We take stock of our existing knowledge foundation that forms the basis for decision making and policies regarding further investments in renewable energy innovations. We point to that there are a number of challenges related to a true identification of the sector and to stimulating the industrial dynamics of the sector. Measurement techniques and data form some of the knowledge foundation we have, but we call for improvements. In particular, activities and barriers regarding investments and investors should be thought into the knowledge foundation we need for wise decision making and policies towards a sustainable transition of the energy system. Current investments are important links to future development of the industry, which makes information on energy investments crucial in the assessment of future potential transition problems and potentials.

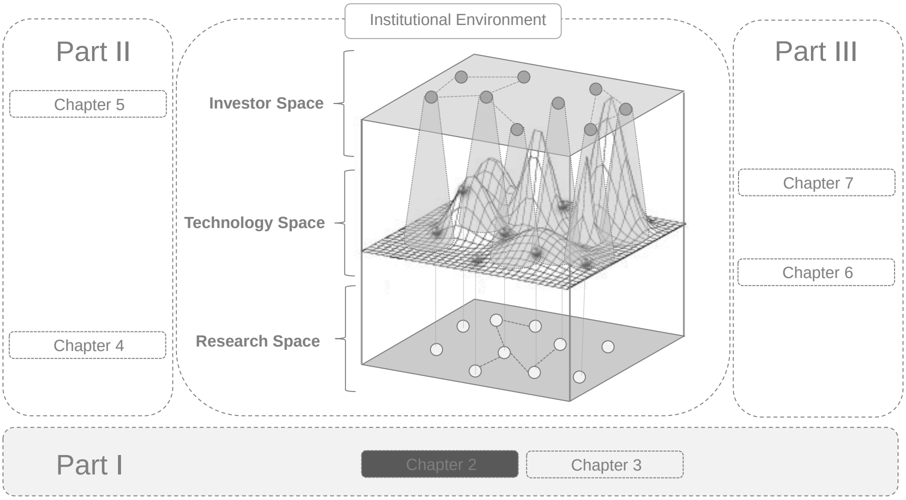
JEL codes: Q42, O33, E01, O16, C82
Keywords: Energy statistics, investments, investors

Preface

Embracing complexity theory and envisioning the the evolution of technology as outcome of a complex system has a first direct implication. A characteristic of nonlinear dynamic systems, is the high sensitivity to initial conditions, where small differences can yield to widely diverging outcomes (Kellert, 1994), making even deterministic systems without random behavior hard to predict with traditional methods. Consequently, to provide and meaningful results and implications during our research endeavors, we have to ensure that we are using the right measure, and are able to do so with high precision. Together with my co-author Jesper Lindgaard Christensen, in this chapter I therefore take stock of our existing knowledge foundation that forms the basis for research, decision making and policies regarding investments technological change in the energy sector, the guiding illustration case along this thesis.

Our aim is to map what we measure up to now, to which extend of precision we do that, and what we do not measure at all, but could and should. We start with providing an overview of current producers of energy statistics and the data they provide, ranging from primary national data on energy production, consumption and emissions to the state of the art concerning indicators of energy innovation systems and their dynamics. Arguing that investments represents a real-time economic response on changing policy, regulatory frameworks and technological opportunities as well as forward looking measure for future technological change and capacity deployment, I illustrate the benefits gained by a more thorough inclusion of investment data for decision making in industry and policy alike. I particularly emphasize the role of investors as a linkage between public policy and firm level activity, discuss the kind of data needed to sufficiently characterize them and fulfill their particular information need to invest in the renewable energy sector. While doing such a mapping, I further point to several types of flaws and difficulties related to getting a statistical overview of investments in the energy sector, and argue they are not just a matter of increasing the existing statistical efforts and precision but caused by more generic difficulties of the energy sector. We identify four interdependent key challenges for the meaningful utilization of data on investments in the energy system, namely (i.) the delimitation of the sector, (ii.) the identification of firms and (iii.) investors active in it, and (iv.) the measurement of industry dynamics and technological change.

Fig. A.1: Positioning the paper in the theoretical framework



Discussing the potential insights for research, policy and industry gained from this data, I advocate for a more thorough inclusion of investment data on different levels, and point to sources and methods to do so. Thereby I do conceptual and descriptive groundwork, broadly facilitating research on different dimensions of technological change to come in later parts of the thesis.

This paper was developed throughout my Ph.D. fellowship. It has been presented in several internal research seminars, and has recently been submitted to the "Journal of Environmental Innovation and Societal Transitions", where it is currently under review.

1 Introduction

Current policy discussions on binding targets for carbon-dioxin emissions are based on two types of knowledge: knowledge on the state of affairs and development in pollution and emissions. This is a sphere for biologists. A second type of knowledge is knowledge on where we are, in which direction we are heading, and in which pace. This is a sphere of statisticians and innovation researchers. It is vital for pursuing evidence based policies in the field that an adequate knowledge foundation for policy discussions is in place. Hence, there is debate around if e.g. energy 2020 targets in the EU can be reached if current investment levels continue as this will produce a funding gap (Forum, 2013; Jacobsson and Jacobsson, 2012). Likewise, for private investors to devote attention and resources to energy in-vestments information on potential investment opportunities is crucial. We therefore discuss the following research question: what is the status of existing statistics and other data available to facilitate policy makers, investors and firms in their decision if and how to invest in the renewable energy sector, and what is needed for these types of decision makers to take well-informed decisions?

The transition from our current, primarily fossil fuel dependent, energy system towards a sustainable one based primarily on renewable resources has high priority on the agenda of most high-income developed countries and many developing countries as well. To facilitate evidence-based decision-making to-wards this transition, there is a need for a solid knowledge foundation at various levels of aggregation. It can be questioned if there is an adequate amount of information available for investors or policy makers, and it is claimed that what is available is often difficult to interpret and compare. This has implications for allocation of capital to RE investments (Inderst et al., 2012). We focus on investments in renewable energy (RE) technologies, including the production, distribution and storage of electricity from renewable and sustainable resources. Our focus area represents only one segment of the broader field of social responsible investments and impact investments, but we believe the case of RE investments is illustrative for problem areas we address and has wider applications.

In major social, technological and economic transitions, finance is an important driving force (Perez, 2010, 2013). Financial markets and their actors, such as institutional investors, banks and venture capital firms, represent the main intermediate link between savings and investments and are pivotal to the smooth functioning of capitalistic economies, propelling economic growth (Rajan and Zingales, 1996), facilitate transition (Bolton and

Foxon, 2015; Geels, 2013; Giddens, 2009) and defining technological trajectories (Dosi, 1990). Consequently, an investor perspective should be an integral component of any strategy towards a sustainable future (Dinica, 2006), and understanding the composition, rationales and information needs of investors is crucial to formulating meaningful RE policies (Hargadon and Kenney, 2011).

In order to identify global trends, formulate policy and assess their impact across countries, comprehensive and comparable statistics on aggregated investments, deployed capacity, energy trade, innovation and other factors are necessary. At a micro level, there is a need to understand which firms develop and deploy RE technologies and which investors provide the necessary capital and why they do so.

We find that one reason for these possible shortcomings is that both the sub-industries and technologies deployed in RE are very heterogeneous. For example, this is true of software based smart-grid solutions, measurement and management of electricity demand, new battery solutions for energy storage and large scale windmill production. Since it is already challenging to identify which firms are part of the RE sector (Shapira et al., 2014), and to what extend they are active in "green" activities, adequately mapping the very heterogeneous group of investors including public agencies, venture capitalists, banks, project financiers and large institutional investors adds to the challenges we face in providing solid statistical evidence useful in decision making processes. Moreover, the knowledge foundation for policies should be based on good indicators and data (Garnåsjordet et al., 2012; Stiglitz et al., 2010), but the statistical system we have faces a number of challenges when moving from accounting past consumption and installed capacity to investments into the innovation and transition of the system.

We further point towards several types of flaws and challenges related to getting a statistical overview of investments in the energy sector, and argue they are not just a matter of intensifying existing statistical efforts and improving precision, but are caused by more fundamental difficulties. We particularly emphasize the role of investors as a linkage between public policy and firm level activity, and we discuss the kind of data needed to sufficiently characterize them and fulfill their particular information needs to invest in the RE sector. This information is important not only in a research context (Grupp, 1998), but also for political and practical reasons. Potentially, the quality and amount of statistics may create virtuous or viscous cycles of investment behavior because investment areas only covered by weak statistical evidence may receive limited attention from investors, which may in turn render fewer incentives for producing better statistics, and *vice versa*.

We proceed as follows. In the next section 2 we provide an overview of the current primary producers of statistics on energy and the available statistics. We include a short discussion on indicators based upon several recent research projects (Borup et al., 2013; Gallagher et al., 2011; Inderst et al., 2012) on this as well as efforts to produce statistics and indicators by OECD (2011a). In section 3 we discuss how investments in energy are different from other investments, and why consequently, particular information on RE is of higher importance or scarcity than in other industries. section 4 focuses on the challenges in measuring energy activities. In sub-chapters we discuss the problems of identifying and delimiting firms, industry dynamics, and technological change. In section 5 we zoom in on the investor landscape of RE. Finally, we summaries the deficiencies we pointed to during the discussion on measurement challenges in RE and discuss how to address these challenges and whether producing comprehensive and adequate RE statistics is realistic. Moreover, we discuss the possible implications of a lack of adequate statistics.

2 Our knowledge foundation of today: existing energy statistics

After a period of declining quality and coverage in energy statistics resulting from the liberalization of energy markets, budget cuts, and lack of expertise (EUROSTAT, 2005), a recent increased interest in energy has led to a rapid improvement of the empirical evidence on energy investments. Energy statistics now cover a wide range of technology fields and countries. The increased interest in measurements of energy production, consumption, and impact has been spurred by the binding targets for RE that many countries adhere to, and ongoing discussions on the extent to which they should sign up for these tar-gets. Moreover, RE now makes up a substantial share of total energy production. This share is rising globally and in some countries much higher than in others. We point in this section to important sources of information on energy consumption, energy innovation, and energy production. In the fifth section we resume a discussion of the available statistics, but in relation to investors and investments in energy.

Energy statistics have been developed in many countries to map the development of the energy systems, especially with regard to energy consumption and energy production, whereas energy innovation is less well covered. Harmonization and measurement is further guided by the "Renewable Energy Directive 2009/28/EC" (EUROSTAT, 2013). Some of the relevant statistics may be found in national accounts; however, this will usually be inadequate in quality and coverage, and much of the information needed for informed decision-making is non-existent. The majority of EU-28 countries also provide more disaggregated data on energy sources produced, such as RE.

International comparisons of such data are important for many reasons, such as in the negotiations on climate emissions and targets for RE production and consumption. There are international organizations that collect and compare national statistics. The Eurostat data on energy R&D is valuable, but operates at a high level of aggregation, rendering analyses of renewable energy somewhat inadequate (Wiesenthal et al., 2012). The primary statistics in the field are collected in a joined and harmonized effort by OECD/IEA[1]/Eurostat and by UNEP. The World Energy Outlook, from the International Energy Agency (IEA), is another example of statistics that cover part of the field, even though it is only based on information from its 28 member (OECD) countries, leaving out a range of countries that are not member of the OECD. The resulting statistical bias is illustrated by the fact that public spending on energy R&D in Brazil, Russia, China, India, Mexico and South Africa totaled 13.6 billion USD, which corresponds to the amount of all the IEA members combined (Gallagher et al., 2011). In Europe, 19 of 27 EU-member states are covered in the IEA statistics, which is a relatively small share; however, the coverage is around 99% of in-vestments when measured in volumes (Wiesenthal et al., 2012).

While we therefore do have some statistics in the area, there is a need to extend the focus beyond input and production, to also pay more attention to environmental impacts. Thus, some observers point out that accelerated rates of technological innovations are needed to cope with environmental challenges (Gallagher et al., 2011; Grubb, 2004). However, what is needed in relation to this is an adequate measurement of how such technologies work, how they impact to alleviate environmental impacts, and how this improved environmental impact relates to the inputs they require. This accentuates the need for a more developed energy innovation statistics than the ones available today.

[1]IEA, International Energy Agency, was established in 1974 as an autonomous entity within the OECD. It was established in the wake of the first oil crisis and had (has) a primary objective related to improve oil supply systems. However, its activities span a wide range and include alternative energy sources.

Whereas RE production technically is possible to measure, even with difficulties, the measurement of environmental impact and the application of energy efficiency technologies pose special challenges. Data must relate to not only improved knowledge on the input side in terms of innovations and R&D in private firms that could have an impact on the environment, but also to the precise measurement of this impact. The fact that the energy market is to a large extent decentralized and a large proportion of RE is not traded on a market further complicates production of adequate statistics on efficient energy usage. For example, photo voltaic, solar heating, thermal heating/heat pumps, wood fuel etc. are extensively used in individual, private households but rarely measured. In addition, although energy efficiency is an important factor in reducing total carbon dioxide emissions, as well as a source of reduced costs for companies, the measurement of energy efficiency is poorly developed (Rennings, 2013).

The development of a sustainable energy system not only requires the environmentally friendly production of energy, but also a more efficient use of it. Energy efficiency is a feature of a wide range of different products and applications. Moreover, Rennings (2013) argues that energy efficiency should be seen as relative to existing practices. This complicates the goal of establishing a general and comparable way of measuring the application of energy efficiency products. It is, however, possible to partially measure energy efficiency, if we measure on a higher level of aggregation. The change in energy consumption compared to GDP change is a rough indicator of energy efficiency and is used as such in statistics compiled by IEA, Eurostat and the OECD. Although these statistics now follow a specific guideline[2], there are technologies that the statistical system is not yet geared to capture, one example being heat pumps.[3] To analyze disaggregated patterns of energy usage across countries and industries, the World Input-Output Database (WIPO, cf. Dietzenbacher et al., 2013; Timmer et al., 2015) could be used as a valuable resource. It provides data on inter-industry input-output relationships (including energy input) of 40 major economies dating back to 1995, and thus can be utilized to capture the effect of technological change and/or policy measures on energy usage, and how this effect might differ across industries and countries.

Regarding empirical evidence on sub-industries, a number of more specialized organizations compile statistics focused on specific sources of RE. For example, the Global Wind Energy Council is the international trade associa-

[2]The Renewable Energy Directive 2009/28/EC

[3]Which, as illustrated by Jurowetzki (2015), is an integral part of e.g. the Danish smart-grid.

tion for the wind power industry and publishes statistics on the global trends, for in-stance, in installed capacity (http://www.gwec.net/global-figures/graphs/). Another example is the European Photovoltaic Industry Association that likewise does specialized studies, market outlooks and statistics. As an umbrella organization for these sub-industry organizations, the European Renewable Energy Council (EREC) represents the entire renewable energy sector and has statistical information based upon national statistics and Eurostat.

A growing interest in more environmentally sustainable energy production has led to further recent attempts to develop indicators and measurement of sustainable production. These include (Kemp and Pearson, 2007), and the OECD (2011b). To take one of these examples, the OECD lists indicators for monitoring green growth including, amongst others, GDP per unit of energy-related CO2 emitted, share of RE in electricity production, RE in percent of energy related R&D and carbon market financing. (OECD, 2011b). In total they list 23 such groups of indicators, many of which have more than one sub-category of indicator. They may in turn be used in statistics, for example, to list ex-ports/imports of RE, employment in energy technology sectors and development of public RD&D budgets (Borup et al., 2013). Generally, indicators are well-developed in some areas, but often suffer from fundamental definitional problems when it comes to transferring indicators to statistics, as we shall discuss later.

It is not the purpose of this article to go into detail with the specific numbers in the RE area, as mentioned above. Rather, we point out what is there, what is missing, and we illustrate two selected issues. First, regarding the European development in RE, figure A.2 shows two primary things: except for a small dip in 2011, a steady increase in both the production of energy from renewable sources and the share of electricity consumption stemming from RE sources,[4] and secondly, that there are vast differences in the contributions from the different sources. Among sub-sources, wind energy has shown the highest growth.

Although not illustrated in figure A.2 just as there is heterogeneity among energy sources, there are vast differences among countries in several respects.

[4] The growth in energy production stemming from renewable sources has been relatively slow and the share of RE production remains at an aggregate level relatively small despite increased investments because there are still also investments in non-renewable installations, which typically are large, capital intensive, and with long operating lives (Geels, 2013). This potentially creates a lock-in of the existing structures where transition to a new system is difficult and it has made some observers denote the renewable energy technologies as "niche-innovations" (Geels and Schot, 2007).

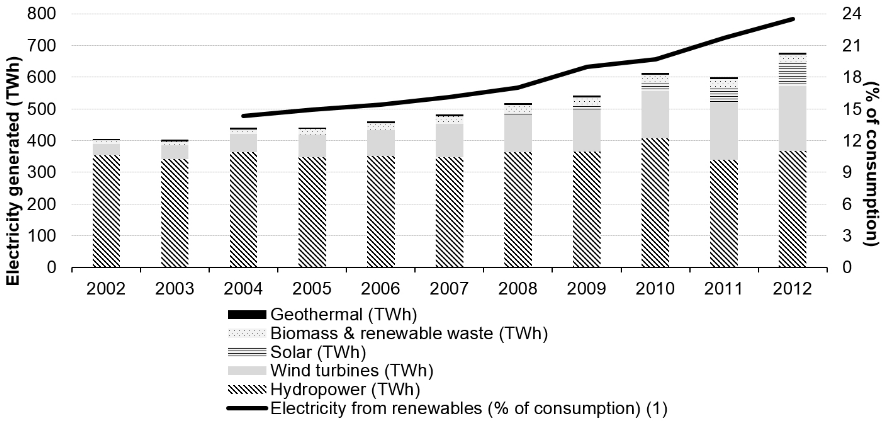


Fig. A.2: Electricity generated from renewable energy sources, EU-28, 2002–12, Source: Eurostat Data

They differ in the share of RE in total energy production and consumption, in the targets the countries have for RE, and in the efforts they pursue. They also differ considerably in the source of RE, which in turn is dependent on natural endowments. Thus, by far the majority of RE sources in Norway, Austria and Sweden is hydropower; Denmark, Ireland and Spain specialize in wind energy; Portugal in solar energy, Italy in thermal heating (due to the volcanic activity in the country). There is also industrial specialization among these countries; for example Denmark in wind energy, Scotland in wave technologies, Germany in photo voltaic etc. The heterogeneity of energy sources and the specialization of certain countries in different forms of energy production not only results in different interests in energy statistics and energy innovation, it also has implications for the specialization and types of relevant investors and investments, a problem area we elaborate on in section 5 on measurement challenges and statistics on the investment side of RE. We showed above that there is vast heterogeneity in the growth within RE (biomass, wind, geother-mal, hydropower etc.) amongst sub-industries, but also between countries in how they specialize in these sub-industries. As a consequence, statistics in this field need to be relatively fine-grained and may render poor information if used on too aggregate a level. While we use the case of RE for illustration, this is likely to be true for other target areas of what is now termed social responsible investments and impact investments (Renneboog et al., 2008b; Sparkes and Cowton, 2004) in complex and diverse sectors, such as global food supply or medical supply.

3 What is special about Investments in Energy?

Understanding investments in the energy sector requires understanding its distinct characteristics (Grubb, 2004). The first such feature of energy investments is that they are highly dependent on systems and infrastructure. The production, innovations and technologies in the sector are often connected to and dependent on other, complementary elements and technologies in the energy sector (Jacobsson and Bergek, 2011). Consequently, changes in one part of the sector are often linked to changes in other parts of the sector and the feasibility of new products and processes depends on their compatibility with the existing energy infrastructure. In many respects it is possible to talk about energy "systems" rather than just "sectors". In such complex and interdependent systems with a number of elements that collectively fulfill a single or various goals (Simon, 1969), the development of new components is compounded by the ex-ante unpredictability of other components' reactions (Fleming and Sorenson, 2001; Frenken, 2006). This perspective has implications for measurement as it accentuates the importance of indicators and statistics on interaction and cooperation in the system. Likewise, it points to the relevance of what might be termed "throughput indicators" (Borup et al., 2013).

Large technological systems usually adapt gradually to changing internal and external needs (Hughes, 1987). However, some features of the energy system are related to the capital-intensity of infrastructure, the institutional setup and industry structure create inertia and lack of abilities to respond to external pressure to change. First, sunk costs and long amortization periods slows down technology adaption, since existing equipment such as power plants and transmission lines are replaced only every couple of decades. Current energy infrastructures in the majority of countries are formed around fossil fuel technologies (gas, oil and coal) and the particular needs of a carbon based energy system, such as centralized energy generation and stable system load. Modern low-carbon technologies often diverge from this paradigm, making them difficult to integrate. Further, the major share of this infrastructure is controlled by large established energy cooperatives with vested interests in preserving the *status quo* in a form of "incumbent capitalism" (Khosla, 2011) by exercising their influence in industry and policy (Hain and Jurowetzki, ming; Tsoutsos and Stamboulis, 2005).

As a consequence, this tendency to preserve the established pat-terns of investments in equipment as well as in research leads to a lock-in of the energy system at its cur-rent state (Unruh, 2000, 2002). Technological progress and economies of scale enjoyed by incumbents further reinforce this process as negative environmental externalities caused by carbon based energy production remain un- or under-priced (Brown, 2001; Rennings, 2000). Regarding measurement, it has been suggested that indicators of energy systems should consider this lock-in, for example by including the R&D budget for fossil fuels (eg. Grubb, 2004) or infrastructure ownership and energy co-operatives' governance structures as an indicator of what could be termed a carbon-lock in. Because the development and integration of new energy technologies typically takes decades, measuring should not only focus on the state of affairs but also on the relevant learning and competence build-up taking place. Similarly, it has been argued that indicators should be forward looking because of large time-lags between actions and consequences and because of the high uncertainty related to the outcome of both present actions and technological developments (Garnåsjordet et al., 2012; Stiglitz et al., 2010). In the next section we discuss this problem and suggest some forward-looking measures of industry and technology development.

Compared to many other industries, the energy industry in many countries is characterized by a heavy involvement, often even dominance and ownership, of the public or semi-public organizations. For many reasons, political as well as economic, energy systems are important policy targets and subject to intense public regulation. Even if public policy and regulations are not directly subject to energy measurement, it provides important frameworks for energy production and consumption. Therefore, measures of public investments and public procurement of energy can also be meaningfully quantified.

Even though the conditions in the RE sector appear to be unique in make-up, some of the characteristics of energy investments can be observed in several other sectors. Examples are the enormous capital intensity of the R&D process and the long amortization time in pharmaceuticals, the reliance on infrastructure and state regulation in telecommunications, and the limited economics of scale and technical complexity of aerospace. Consequently, this macro-, meso and micro heterogeneity of industry dynamics calls for lower levels of aggregation in quantitative analyses than, for example, in "manufacturing". Hence there is a need for more fine-grained data.

With the findings in this section and in the second section in mind, it is clear that the pure definition of renewable energy remains unclear, and therefore a number of studies focus on indicators Andersen (2006); Kemp and Pearson (2007). The boundaries of the technologies and the industry as such mentioned in figure A.2 are not clear when considering their complexity and inter-dependencies as well as the dual use of RE technologies and conventional technologies in the same product, equipment, or process. A number of other problems add to the blurred definitions, such as whether energy storage, transmission, and energy efficiency measures should be part of the industry.

In summary, we argue that new energy technologies are often integrated in a highly complex and interdependent energy system (Jacobsson and Bergek, 2011). The systemic character of energy production in turn poses challenges to investors in assessing the opportunities of such new technological developments, as investment due diligence not only requires deep and interdisciplinary technological knowledge but also knowledge of the system in which opportunities regarding new products and processes should be implemented. Moreover, RE technologies are in most cases very capital intense in development as well as deployment (Burer and Wustenhagen, 2009), and consequently require long term capital commitment (Kenney, 2011). Finally, investment opportunities and their returns are heavily dependent on state regulations on different levels, and are thus subject to high policy risks (Astolfi et al., 2008).

4 Measurement Challenges in the Renewable Energy System

4.1 Industry heterogeneity

Above we pointed to definitional and system characteristics of energy investments and the problems these characteristics pose for investments and measurement. In this section we emphasize a dynamic perspective as we point to different delimitations of the industry in different stages of the evolution of energy technologies and sub-industries. Again, sub-industries display great heterogeneity in this respect. Some industries, such as windmill production, have already reached a high degree of maturity, are dominated by multinational enterprises, and are characterized by enormous capital intensity in development and production. Other industries such as fuel cells, smart grid and energy storage solutions are in early phases of their development without an established dominant design, allowing for experimentation, disruptive innovation and entrepreneurial activities but also substantial technological and market risk. In addition, applied technologies differ substantially in their relevant characteristics, not only between but also within industries. To take one example, there are very different capital requirements, risk projections and potential investor characteristics for traditional technologies in comparison with vertical axis windmill technologies. Similarly, the competences involved in on-shore and off-shore wind production differ substantially.

Figure A.3 illustrates the multitude of actors involved in the financing of energy investments as well as the industry and technology landscape in different stages of development and maturity.[5] The upper half of the figure depicts the actors directly involved in the process of technology development, which in this model commonly commences in university and research labs, then is picked up by entrepreneurs or corporate R&D, diffused in the market and finally commercialized in full scale by large enterprises. Regarding the corresponding investors in the bottom part of the figure, they are specialized and ordered according to their investment capacity and willingness to engage in investments of different maturity and risk pro-files. While capital requirements usually increase during the process of technological evolution they do not necessarily have proportional impact as small investments in early stages can have disproportional catalytic effects.

The above process perspective on technology development and corresponding types of actors, in-vestments and investors offers valuable insights for understanding the dynamics of RE investments and in turn for policy making. First, mismatches between actor and technology characteristics, on the one hand, and on the other hand, investor capabilities and preferences can cause financial bottlenecks at any of these stages and seriously jeopardize further technology development. Commonly such bottlenecks are referred to as "valleys of death" in which technologies "die" due to underinvestment. According to figure A.3, valleys of death are likely to occur for RE technologies in the post-lab but pre-market stages. To advance RE technologies from the lab to a full-scale demonstration project can require substantial amounts of cap-ital. At the same time, public funding to fund early research gets scarcer at this stage. Hence, scaling up RE technologies often reaches another potential valley of death, when the capital requirements exceed the capacity of early stage investors but technology risk is still unacceptably high for most institutional investors with suitable investment capacity. Addressing such market and system failures by preventing mismatches requires disag-

[5] For the sake of simplicity, the figure depicts a linear innovation and technology development process, where inventions originate from the outcomes of basic research, are adopted by corporate applied R&D followed by demonstration and finally diffusion in the market. Nowadays it is well understood that technology development is by no means linear but characterized by feedback loops between the different stages (Freeman, 1996), better described as a "chain-linked model" (Kline and Rosenberg, 1986).

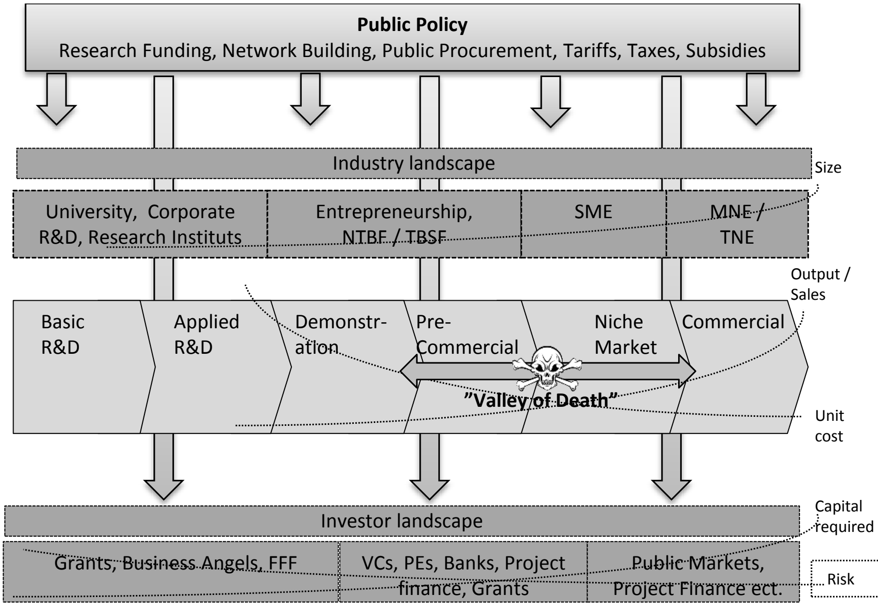


Fig. A.3: Segmentation of predominant firms and investors. Source: adapted from Wüstenhagen and Menichetti (2012) and Grubb (2004)

gregated information on firm, technology and investor characteristics. However, because this information is interrelated and not confined to the energy system, for example the identification of the firm population, deployed technologies and RE investments, it remains problematic to establish adequate measurement tools hence a comprehensive knowledge foundation for investments into that RE sector. In the remainder of this section we will therefore discuss the challenges we face to identify and measure firms and technologies.

4.2 Identifying RE firms

The boundaries of industries are traditionally defined by their industry classification, such as NACE, SIC etc. based on the activities of firms. It should, in principle, be possible to identify the population of firms within an industry using their industry classification. However, a number of problems for the accurate identification of an industry remain. Some of these problems stem from the imprecision of classifications, some stem from more generic problems in assigning firms to specific industries (Christensen, 2013; Klitkou, 2013; Shapira et al., 2014). One of the most severe problems relate to the cross-disciplinary and cross-industrial character of activities, which means that firms often have activities within several different industries. Such measurement problems are multiplied when considering narrow segments of industries such as RE. Many firms outside the energy industry perform activities within RE, but firms in conventional energies (oil, gas etc.) are also very active in RE. The option of reporting several industry codes to account for multiple activities in practice does not alleviate these problems, and generally it is not mandatory for firms to report disaggregated levels of activities. As a consequence, register-based industry definitions of RE are highly uncertain. This has led Wiesenthal et al. (2012) to suggest a bottom-up approach to measuring R&D investment low-carbon energy technologies, where additional information and estimations are included to come up with a more reliable estimate of R&D investments. However, it remains difficult to delimit the industry in terms of the population of firms, which leaves us with problems in the production of reporting based statistics and surveys. (Shapira et al., 2014) describe flaws in existing methods to identify "green" firms and suggest identifying the population of "green" firms by way of a search-based method where textual searches of business databases produce information on the firms who have "green" products, independent of their SIC classification. However, the majority of the fundamental problems remain.

4.3 Measuring Industry Dynamics and Technological Change

We posited above that currently we have highly inadequate statistics in this field and we face a number of challenges in measuring investments in energy innovation. For example, the study by Gallagher et al. (2011) points out that there is an urgent need to improve the quality of energy innovation statistics in a number of areas including measuring a) the R&D in private firms; b) technology specific investments; c) non-OECD country statistics. It has, though, been increasingly common and important to also measure industry dynamics in terms of the innovation activities in the industry (Grupp, 1998). Therefore, we focus this section on the measurement of energy innovation. We approach this by discussing three types of indicators that are usually used in this connection; R&D expenditures, patents and innovations.

Indicators of innovation inputs in terms of R&D statistics and of output in terms of patents are *valua-ble*, and often used, in innovation studies. However, they do not capture all innovation inputs and outputs. Similarly, national accounts measure factors like production volumes, energy sources and energy prices. These accounts are important, but largely inadequate for energy innovation. Hence, we are currently in a position where the statistics on investments in innovation and the output of innovation processes in the industry are based on inadequate indicators, especially when it comes to investments beyond the RD&D phase. Organizations such as The OECD have compiled information on "green" innovations in special studies[6]that do compare data, for instance on patents, for member countries as well as discuss other measurement issues. Likewise, several organizations now perform a more systematic registration of "green" patents, illustrated by the fact that the EPO now has a patent tag covering technologies for mitigating climate change. Patents are relevant from an investment perspective because patents have now become an important parameter in both the decision to invest and in the subsequent possibilities to exit from the investment.

Another source of information is survey-based methods. For example, in their national innovation surveys (Community Innovation Surveys), a number of countries implemented questions on environmental issues more broadly, some of which are informative regarding energy innovation as well. Survey-based approaches to identifying green firms and uncovering industry dynamics in terms of innovation activities suffer from disadvantages as well, such as their general weaknesses in response rates and establishing the relevant initial sample. The empirical evidence on innovation produced from survey-based approach-es also suffers from comparability problems, lacks harmonized definitions of energy innovation and fails to make a clear delineation of the energy sector, as many firms are involved in energy innovations even if belonging to another main industry in the official classifications. This makes it difficult to analyze the total activities (Shapira et al., 2014).

In this section, we argued that data on public and private sector innovation activities are important for technology forecasting, as a basis for public authorities to decide how to allocate research grants, for investors to spot promising investment targets, and for firms to allocate innovation budgets. Although the R&D statistics and patent statistics do indicate aspects of industry dynamics, the measurement of industry and technology evolution poses additional challenges. We discussed innovation measurement in RE and pointed out that innovation statistics, and other measures of industry dynamics, are relatively new and not yet fine-grained enough to make it suitable for comprehensive studies of RE innovation.

[6]For example, OECD, 2008. Environmental Policy, technological innovation and patents. OECD studies on environmental innovation, Paris, and OECD, 2011. Fostering innovation for Green Growth, OECD Green Growth studies. OECD Publish-ing, Paris.

5 Investors and Investments

As illustrated above, there exists a variety of aggregated data on certain measurable aspects of the global energy system. Most assessments of policy measures as well as the regional, national and global progress of CO^2 reduction and RE agendas are illustrated by statistics on installed capacity or electricity generated from RE sources (Jacobsson and Lauber, 2006; Toke et al., 2008). However, in line with one stream of research in energy policy studies (e.g. Dinica, 2006; IEA, 2003; Wüstenhagen and Menichetti, 2012), we argue for the need to additionally consider more emphasis on investment data. We propose this focus for several reasons. First, investment represents real-time responses of industry and investors, enabling us to predict future technological progress and installed capacity. Second, RE investments differ in their characteristics and impact, as they are highly interdependent (systemic) (Jacobsson and Bergek, 2011). A lack of particular investments can cause bottlenecks and "valleys of death", which may jeopardize further development and deployment of technologies. Third, the investment patterns in society mediate resources from savings to future production, as underscored in the introduction. Hence, investment pat-terns are the primary predictors of possible industrial transformation. We start with a discussion on the basic principles related to financing RE. We then take stock of existing information sources for decisions on energy investments, which span a wide array of different compilations of statistics of varying quality.

In general, investors primarily aim to adjust the risk-adjusted returns of their investments. The risks investors commonly consider are related to the firm/project invested in, the technology deployed, the market it sells in, and policies that might influence it. Where the first is specific to the investment, the latter are systemic.[7]As a simple rule, investors will require higher returns for riskier investments in order to maintain a certain level of average returns. Yet, it is seldom that simple. First, not only the average, but also the variance of returns matter. Assuming investors *per se* are risk averse, given the same risk adjusted returns, they will tend to choose the investment with lower variance. Second, different investors will have different risk preferences and specialize in investments with certain risk-return-variance levels. For exam-

[7]It must be mentioned that all systemic risks are usually high in RE investments due to the high complexity and in-terdependencies of deployed technology, price shocks on the market, and high regulation and policy influence. Prices on substituting products/energy have historically had a huge impact, best illustrated by the upsurge of RE after the oil prices surged in 1973 and 1979.

ple, while institutional investors such as pension funds usually show a very low risk tolerance and require only modest returns, venture capitalists invest in highly risky targets but therefore require ex-extraordinary returns. Third, a long tradition of research on behavioral finance tells us that this risk/return assessment is less of an objective optimization process by fully rational agents, but rather a heuristic one by agents acting under "bounded rationality" (Simon, 1955). Since the set of information needed to fully assess risk adjusted returns on an investments in most cases is incomplete and the agents processing power are limited, their judgment will often be based on simple heuristics, rules-of-thumb and intuition (Tversky and Kahneman, 1974). Further, this judgment is also subject to a set of cognitive biases (McFadden, 2001) caused by the agents' beliefs, historical experiences and social influences. Thus, investment decisions are made based on "perceived risk", which will differ between agents according to their existing knowledge, available information and cognitive biases. Besides optimizing the perceived risk-adjusted returns of their portfolio, some investors in RE also integrate social, environmental and ethical considerations into their decision making (Renneboog et al., 2008a,b). Moreover, in the financial literature, financial constraints are said to stem from problems derived from asymmetric information between borrowers and lenders (Akerlof, 1970). Because energy systems are highly integrated and interdependent, these problems are likely to be multiplied.

Decision making under uncertainty, bounded rationality and asymmetric information requires investors to specialize in certain types of investments, firms or technologies. While venture capitalists usually prefer to invest in early stage technologies with high growth potential, most PE are not willing to bear high technology risk; banks and prudent institutional investors will only invest in mature and "safe" firms and technologies, but they therefore require lower returns and can cope with higher investment sums. Consequently, information needs as well as reactions to policy measures are idiosyncratic among investor types. An institutional investor might be more concerned about indicators of individual and systemic in-vestment risk, while venture capitalists focus on long-term market potential. The heterogeneity of technologies and industries associated with RE obviously leads to a higher need for investor heterogeneity compared to other industries.

To sum up, investors care about risk-adjusted returns and their variance, have different risk tolerance, and assess individually "perceived risk" under bounded rationality. Though still subject to imperfect information and cognitive biases, this assessment will become more precise when investors undertake the effort of gathering a more complete set of information on investments and context, and applied heuristics improve with increasing investment experience and knowledge relevant for the particular investment. Therefore, capital markets are characterized by a division of labor and specialization, which is expedient when investors need to cope with complex and asymmetric information in the market. Investors might specialize in investments in firms with certain characteristics (start-ups, mature firms), deployed technologies (ICT, biotech, RE), asset classes (VC, PE, loans, project finance), risk profiles (low, high) etc. Specializing in one or more of these investment characteristics results in a particular set of relevant in-vestment targets and information needed for their assessment. Thus, we argue that to obtain a proper analysis and understanding of investments in RE or elsewhere, we need a nuanced and disaggregated reflection of the structural composition of investors and investments in our statistical evidence.

To fulfill this objective we face a couple of challenges. As discussed earlier, the diversity of the RE sec-tor makes it challenging to draw its boundaries and decide which technologies and firms should be assigned to it. Consequently, quantifying investments in RE faces the same problem. Further, the majority of investors invest in multiple industries, and are thus equally hard to identify. While there exist some investors exclusively committed to RE such as politically motivated associations, endowments and foundations, for most others, such as institutional investors, RE represents only a small share of their portfolio. Likewise, even if the venture capital investors, for example, have gained interest in the clean tech industry generally, and energy in particular, the number of dedicated venture capital funds indicates that they are a very small minority.[8]

Currently, reasons such as limited mandatory disclosure of certain finance vehicles limits available in-formation on investments to sporadic studies and reports by national and international energy agencies (e.g. IAE, IPCC, UNEP), associations, NGOs, research institutes promoting the sustainable transition (e.g. IIASA), and financial institutions and information providers (e.g. Bloomberg New Energy Finance, Reuters). Such reports on RE usually provide investment data on different levels of disaggregation, which may be broken down by technology, asset class, region and over time. They often differ in their definition and measurement of RE-, sustainable-, clean-, or green-investments, yet they provide some valuable insights. We briefly illustrate such statistics. An example of such statistics is provided in figure A.4,

[8] Moreover, after a period with increasing interest from investors in this area, there are now indications of less attention from funds to clean tech investments as also indicated by figure A.4.

which depicts the development of global investments in RE by asset class and offers some broad indications on tendencies in energy investments.[9]

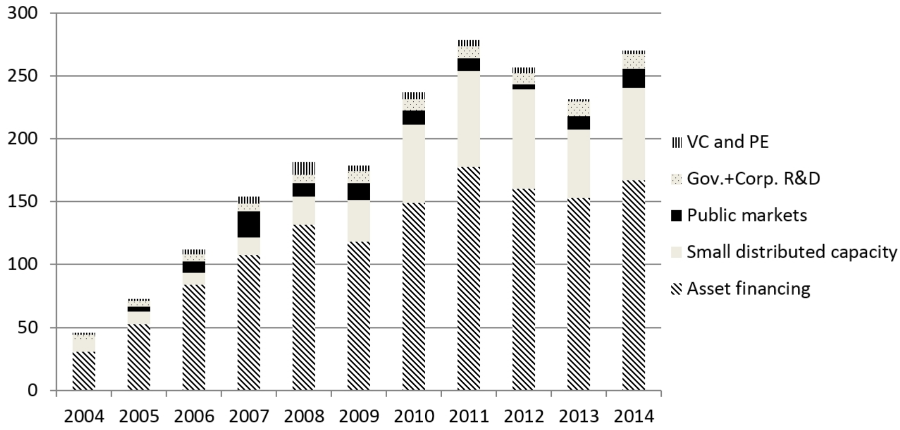


Fig. A.4: Global new investments in RE by asset class, 2004-2014, BN USD, source: UNEP

Among others, it illustrates the predominance of asset financing[10] stemming from the enormous capital intensity of the energy sector. In contrast, early stage financing sources like venture capital and government R&D remain a small fraction of the total investments. Atypical for capital intense industries, public market finance is also of minor importance in RE. In spite of the small share of total investments, early stage public R&D investments are said to have disproportionally high impact on the development of radically new technologies, as they fund early stage research that is often outside the scope of private investors (Ebersberger, 2005). It should be noted that the financing instrument does not necessarily reflect a specific financing source or agent. Even if there is a specialization and division of labor on capital markets, agents may still use multiple financing instruments simultaneously.

As discussed earlier, investments in RE are subject to a set of market failures and system failures, of which some are generic and some stem from the particularities of the energy sector. Aggregated investment accounts such as the one in Figure 3 and Figure 3 at first glance might serve as a good indicator for the efficiency of such measures. However, while the question of how and where investments in RE are allocated across countries, industries and technologies has received growing attention in recent years, the question of

[9]See Geels (2013) for a more comprehensive illustration of the available investment statistics produced by the above-mentioned organizations.
[10]A form of debt finance backed by asset collateral.

who ultimately invests and why they do so has received much less attention. During the course of this section, we argued that applying an investor perspective reveals a set of reasons why more granular policy measures as well as indicators are needed.

The relevant question is where such needed information might be available for policy, research and investors. Besides the already mentioned reports by the IAE, UNEP, EUROSTAT, Bloomberg etc., investor organisations such as the European Venture Capital Association (EVCA) provide an overview of RE in-vestments on different levels of aggregation. While it remains a problem to develop an adequate methodology to identify firms active and technologies deployed in the RE realm, there are indeed some sources of exhaustive micro data on investments, and means of identifying investors. Since data on equity deals are of high value for professional investors, who are willing to pay for it, there exists a huge variety of commercial databases on different forms of equity investments, such as VC, PE, M&A and FDI. Popular examples are Thompson & Reuters "VentureONE", Bureau van Dijk's "ZEPHIR" or S&Ps "CapitalIQ" investments databases. They usually contain rich longitudinal data on investment target, investor and investment characteristics. In addition to common industry classifications such as NACE codes, they often contain their own sector or industry classifications, including classes such as "RE", "energy transmission" and the like, which might be used to identify RE firms and investments, although they still suffer from the above-mentioned problems of precise classification procedures. Alternatively, free open access finance and business databases such as "crunchbase" have significantly improved in accuracy and coverage over the last few years, and nowadays can be seen as a true alternative to the commercial databases. However, because of the structure of most private equity, these databases only contain information on the direct shareholder (general partner), and not the initial provider of capital (limited partner). While such in-formation was hard to obtain due to corporate secrecy and very limited disclosure requirements, some newer databases have started to collect information on the true origin of equity investment capital, the limited partners. Among the few examples are the "PreQuin" investor intelligence and the DowJones "LP Source" database.

While there exists plenty of information on equity investments, limited disclosure regulations make data on debt forms of finance very hard to obtain. One of the few databases is Thomson Reuters "DealScanner", which provides information on the global syndicated bank loan market, which, though important, is only a small fraction of overall debt finance. Since the major share of investments in RE actually takes place in the form of (debt based) project finance, such data is urgently needed. One exception providing detailed information on energy projects, installations, power plants and their investors is the commercial "Power" database provided by GlobalData.

To sum up, the heterogeneity of investors and investment targets calls for micro-level data able to clearly identify them and isolate their particular rationales. Overly aggregated statistics are likely to "average out" possible problems and opportunities alike. Even though there is micro-level information on most types of RE investments, it usually has to be obtained from a variety of disconnected and mostly commercial data sources.

6 Outlooks and challenges

Finance of energy innovation is an important part of the overall discussion of different, more environmentally friendly modes of production. Policy is instrumental in such transitions as underscored in several papers (Bolton and Foxon, 2015; Jacobsson and Jacobsson, 2012; Perez, 2013). The advancement of actions towards establishing green, sustainable production is, however, dependent not only on political will, but also on whether empirical evidence in the area is commonly agreed upon and of a good standard. Policies for unleashing the potentials of green investments was not our primary focus area but indirectly the empirical evidence we have is important in relation to policy as well as it provides the knowledge foundation for societal transition. In this sense also the data we produce and the statistical system we install are subject to value premises and choices based on societal interests (Garnåsjordet et al., 2012). We focused instead on a particular aspect of this discussion as we highlighted the state of affairs and remaining challenges in our measurement of RE and RE investments. It was found that despite recent improvements we are still not in a position to fully understand RE investments using existing statistical sources. Several areas of empirical evidence need improvements.

Among the deficiencies in the current available empirical evidence on RE, we firstly pointed out that the lack of historical, publicly available data addressing RE investment risks is one of the greatest challenges in engaging untapped capital. For example, there is an immediate need for publicly available performance data for investments in RE technologies both within and outside of equipment warranty periods. Additionally, historical data on default rates by the energy purchaser are seen as critical to assessing creditor risks.

A second general requirement for statistics is that we need to recognize the interdependent character of the energy system, which calls for indicators oriented towards throughput and interactions among agents in the system. We are even not sure how to delineate the energy sector as activities span across traditional industrial classifications, which in turn makes it difficult to produce adequate statistics (Shapira et al., 2014) but definitions and statistics in fact also impact the allocation of investments (Inderst et al., 2012).

A third area in which more empirical data is needed is on the investments and investors. A number of much-needed information was pointed to in figure 5, ranging from the identification of investors to the micro-level information on the investments. Fourth, by far the majority of statistics on energy production and consumption covers already-produced and -consumed energy. Because of the intense discussions on climate change and other environmental challenges and problems, a number of scenarios for the future have been established as well. RE is characterized by limited storage possibilities; therefore statistics rarely reflect a stock or potential future production trend. The installed capacity will, of course, reflect future production, but generally we point to the need for other and more forward-looking indicators and statistics. We think that such indicators should also give us a picture of how technologies are likely to evolve. Even though we are skeptical about reliance on technologies to “save the planet”, we do believe that predictions about technological evolution are important to statistics on energy. In turn, such statistics are important as a platform for informed decision making, both for investors and policy makers.

It is unlikely that the statistical profession will ever be able to cover all parts of our even non-exhaustive wish list above but, although it is an ambitious requirement for future standards of data to solve all of these problems, steps towards a better statistical understanding of the (financial) dynamics of the industry require that some of these issues be addressed. We would also argue that because the energy system is undergoing changes and because it is subject to heavy political discussions and influence, the statistical system itself needs to be dynamic and capable of adapting to the needs of users.

References

Akerlof, G. A. (1970). The market for lemons: Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3):488–500.

Andersen, M. M. (2006). Eco innovation indicators. Technical report.

Astolfi, P., Baron, S., and Small, M. J. (2008). Financing renewable energy. *Commercial lending Review*, 23(2):3–8.

Bolton, R. and Foxon, T. (2015). A socio-technical persperctive on low carbon invstment challanges - insights for uk energy policy. *Enviromental Innovation and Social Transistion*, 14:165–181.

Borup, M., Klitkou, A., Andersen, M. M., Hain, D. S., Christensen, J. L., and Rennings, K. (2013). Indicators of energy innovation systems and their dynamics. a review of current practice and research in the field: Radar report. Eis radar report, EIS - Strategic research alliance for Energy Innovation Systems and their dynamics.

Brown, M. A. (2001). Market failures and barriers as a basis for clean energy policies. *Energy policy*, 29(14):1197–1207.

Burer, M. J. and Wustenhagen, R. (2009). Which renewable energy policy is a venture capitalist's best friend? empirical evidence from a survey of international cleantech investors. *Energy Policy*, 37(12):4997–5006.

Christensen, J. L. (2013). The ability of current statistical classifications to separate services and manufacturing. *Structural Change and Economic Dynamics*, 26:47–60.

Dietzenbacher, E., Los, B., Stehrer, R., Timmer, M., and De Vries, G. (2013). The construction of world input–output tables in the wiod project. *Economic Systems Research*, 25(1):71–98.

Dinica, V. (2006). Support systems for the diffusion of renewable energy technologies – an investor perspective. *Energy Policy*, 34(4):461–480.

Dosi, G. (1990). Finance, innovation and industrial change. *Journal of Economic Behavior & Organization*, 13(3):299–319.

Ebersberger, B. (2005). *The impact of public R&D funding*. VTT Technical Research Centre of Finland.

EUROSTAT (2005). Energy statistics manual. Technical report, EUROSTAT.

EUROSTAT (2013). Energy from renewable sources: Statistics explained. Technical report, EUROSTAT.

Fleming, L. and Sorenson, O. (2001). Technology as a complex adaptive system: evidence from patent data. *Research Policy*, 30(7):1019–1039.

Forum, W. E. (2013). The green investent report. the ways and means to unlock private finance for green growth. Technical report, Geneva, Switzerland.

Freeman, C. (1996). The greening of technology and models of innovation. *Technological forecasting and social change*, 53(1):27–39.

Frenken, K. (2006). Technological innovation and complexity theory. *Economics of Innovation and New Technology*, 15(2):137–155.

Gallagher, K. S., Anadon, L. D., Kempener, R., and Wilson, C. (2011). Trends in investments in global energy research, development, and demonstration. *Wiley Interdisciplinary Reviews: Climate Change*, 2(3):373–396.

Garnåsjordet, P. A., Aslaksen, I., Giampietro, M., Funtowicz, S., and Ericson, T. (2012). Sustainable development indicators: from statistics to policy. *Environmental Policy and Governance*, 22(5):322–336.

Geels, F. (2013). The impact of the financial-economic crisis on sustainability transitions: Financial investment, governance and public discourse. *Environmental Innovation and Societal Transition*, 6:67–95.

Geels, F. W. and Schot, J. (2007). Typology of sociotechnical transition pathways. *Research Policy*, 36(3):399–417.

Giddens, A. (2009). *The politics of climate change*. Polity Press, Cambridge, UK.

Grubb, M. (2004). Technology innovation and climate change policy: an overview of issues and options. *Keio economic studies*, 41(2):103.

Grupp, H. (1998). *Foundations of the economics of innovation: theory, measurement, and practice*. Edward Elgar.

Hain, D. S. and Jurowetzki, R. (forthcoming). Incremental by design? on the role of incumbents in technology niches - an evolutionary network analysis. *Journal of Evolutionary Economics*.

Hargadon, A. and Kenney, M. (2011). Venture capital and clean technology: Opportunities and difficulties. BRIE Working Paper, Berkeley.

Hughes, T. P. (1987). *The Evolution of Large Technological Systems*, pages 51–82. The MIT Press.

IEA (2003). World energy investment outlook. Technical report, International Energy Agency.

Inderst, G., Kaminker, C., and Steward, F. (2012). Defining and measuring green investments: Implication for institutional inevstors' asset allocation. OECD Working Papers on Finance, Insurance and Private Pensions 24, OECD Publishing.

Jacobsson, R. and Jacobsson, S. (2012). The emerging funding gap for the European energy sector?will the financial sector deliver? *Environmental Innovation and Societal Transitions*, 5:49–59.

Jacobsson, S. and Bergek, A. (2011). Innovation system analyses and sustainability transitions: Contributions and suggestions for research. *Environmental Innovation and Societal Transitions*, 1(1):41–57.

Jacobsson, S. and Lauber, V. (2006). The politics and policy of energy system transformation? explaining the german diffusion of renewable energy technology. *Energy Policy*, 34(3):256–276.

Jurowetzki, R. (2015). Unpacking big systems - natural language processing meets network analysis - a study of smart grid development in denmark. *SPRU Working Paper Series. ISSN 2057-6668. Available at www.sussex.ac.uk/spru/swps2015-15*, 2015-15:1–36.

Kellert, S. H. (1994). *In the wake of chaos: Unpredictable order in dynamical systems*. University of Chicago press.

Kemp, R. and Pearson, P. (2007). Final report mei project about measuring eco-innovation. *European Environment*, pages 1–120.

Kenney, M. (2011). Venture capital investment in the greentech industries: a provocative essay. In Wüstenhagen, R. and Wuebker, R., editors, *Handbook of Research on Energy Entrepreneurship*, page 214. Cheltenham, UK: Edward Elgar Publishing.

Khosla, V. (2011). Black swan thesis of energy transfomation.

Kline, S. J. and Rosenberg, N. (1986). An overview of innovation. In Landau, R. and Rosenberg, N., editors, *The positive sum strategy: Harnessing technology for economic growth*, volume 275, page 305. National Academy Press Washington, DC.

Klitkou, A. (2013). The challenge of classifications of technologies and products. In Borup, M., Klitkou, A., Andersen, M. M., Hain, D. S., and Lindgaard, J., editors, *Indicators of energy innovation systems and their dynamics*, pages 41–46.

McFadden, D. (2001). Economic choices. *American Economic Review*, pages 351–378.

OECD (2011a). Oecd statistics.

OECD (2011b). Towards green growth: Monitoring progress. Technical report.

Perez, C. (2010). Technological revolutions and techno-economic paradigms. *Cambridge Journal of Economics*, 34:185–202.

Perez, C. (2013). Unleashing a golden age after the financial collapse: Drawing lessons from history. *Environmental Innovation and Societal Transitions*, 6:9/23.

Rajan, R. and Zingales, L. (1996). Financial dependence and growth. Technical report, National Bureau of Economic Research.

Renneboog, L., Ter Horst, J., and Zhang, C. (2008a). The price of ethics and stakeholder governance: The performance of socially responsible mutual funds. *Journal of Corporate Finance*, 14(3):302–322.

Renneboog, L., Ter Horst, J., and Zhang, C. (2008b). Socially responsible investments: Institutional aspects, performance, and investor behavior. *Journal of Banking & Finance*, 32(9):1723–1742.

Rennings, K. (2000). Redefining innovation–eco-innovation research and the contribution from ecological economics. *Ecological Economics*, 32(2):319–332.

Rennings, K. (2013). The challenge of energy efficiency innovations. In Borup, M., Klitkou, A., Andersen, M. M., Hain, D. S., and Lindgaard, J., editors, *Indicators of energy innovation systems and their dynamics*, pages 41–46.

Shapira, P., G., A., Klochikhin, E., and Sensier, M. (2014). Probing 'green' industry enterprises in the uk: A new identification approach. *Technological Forecasting and Social Change*, 85:93–104.

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1):pp.99–118.

Simon, H. A. (1969). *The sciences of the artificial*, volume 136. MIT press.

Sparkes, R. and Cowton, C. J. (2004). The maturing of socially responsible investment: A review of the developing link with corporate social responsibility. *Journal of Business Ethics*, 52(1):45–57.

Stiglitz, J. E., Sen, A., Fitoussi, J.-P., et al. (2010). Report by the commission on the measurement of economic performance and social progress. *Paris: Commission on the Measurement of Economic Performance and Social Progress*.

Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R., and Vries, G. J. (2015). An illustrated user guide to the world input–output database: the case of global automotive production. *Review of International Economics*.

Toke, D., Breukers, S., and Wolsink, M. (2008). Wind power deployment outcomes: How can we account for the differences? *Renewable and Sustainable Energy Reviews*, 12(4):1129–1147.

Tsoutsos, T. and Stamboulis, Y. (2005). The sustainable diffusion of renewable energy technologies as an example of an innovation-focused policy. *Technovation*, 25(7):753–761.

Tversky, A. and Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *science*, 185(4157):1124–1131.

Unruh, G. (2000). Understanding carbon lock-in. *Energy policy*, 28(12):817–830.

Unruh, G. (2002). Escaping carbon lock-in. *Energy Policy*, 30(4):317–325.

Wiesenthal, T., Leduc, G., Haegeman, K., and Schwarz, H.-G. (2012). Bottom-up estimation of industrial and public r&d investment by technology in support of policy-making: The case of selected low-carbon energy technologies. *Research Policy*, 41(1):116–131.

Wüstenhagen, R. and Menichetti, E. (2012). Strategic choices for renewable energy investment: Conceptual framework and opportunities for further research. *Energy Policy*, 40:1–10.

Paper B

The Small, the Young and the Innovative. A Panel Data Analysis of Constraints on External Innovation Financing

Daniel S. Hain[†] and Jesper Lindgaard Christensen[†]

[†] *IKE, Department of Business and Management, Aalborg University, DK*

The layout has been revised, and a preface not included in the original article has been added.

Abstract

Access to external financing represents a critical factor in determining industrial evolution and technical change as well as firm's ability to survive, grow, and engage in innovative activities. However, firm characteristics such as being young, small and engaged in innovation projects, are said to cause information asymmetries between financiers and finance seekers, making them less likely raise necessary external capital to fund innovation projects. Yet, there is little known about how different combinations of these characteristics affects their access to external financing and how contextual, time-variant factors matter. Deploying a two-stage Heckman probit model on a panel data set spanning the period 2000-2013 and covering 1,169 Danish firms, we test hypotheses derived from the literature regarding the impacts of firms structural, behavioral and outcome characteristics on the firm's likelihood to get constrained in their access to external innovation finance. We find that indeed the type of innovation matters, but in a nuanced way. While incremental innovation activities have little negative effect on the access to external finance, radical innovation activities tend to be penalized by capital markets. This appears to be particularly true for small innovators. We link these findings to how capital markets assess information flows.

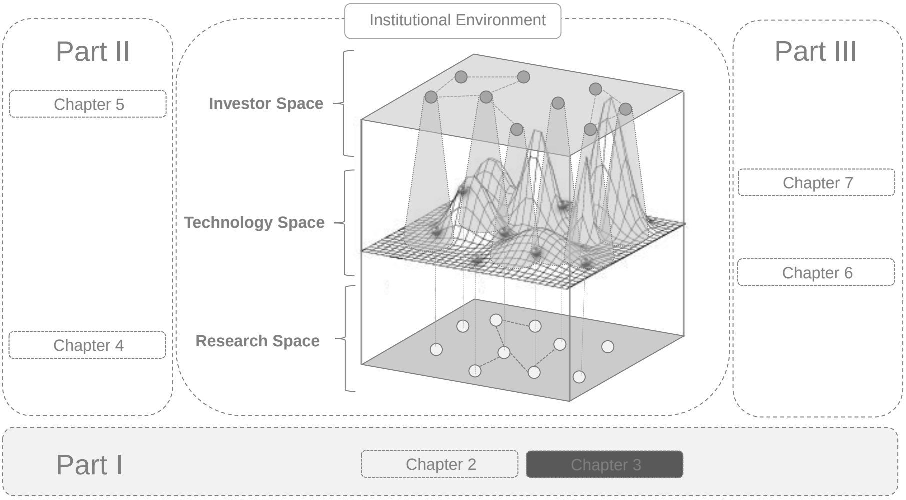
JEL classification: O31, G23, G24, L25
Keywords: Financial constraints, financing innovation, asymmetric information

Preface

Before exploring further the network dynamics of industrial change, in this chapter my co-author Jesper Lindgaard Christensen and I do groundwork by first investigating some more generic issues of financing the essence of technological change, innovation. In detail, at the Danish context I empirically study what enables firms, some of the the main carriers of innovation (Schumpeter, 1942), to access external finance. Generally, access to such external sources of funding represents a critical factor in determining their ability to survive, grow, and engage in innovative activities (Beck and Demirguc-Kunt, 2006). Yet, it is broadly accepted that investments in innovation *per se* appear to embody certain characteristics making them substantially different from other investments (Hall, 2010). From a financier perspective, investing in radically innovative firms *vis-á-vis* their not or only moderately innovative counterparts is foremost associated higher information asymmetries between firm and finance, and related with higher risk and uncertainty of investment outcomes (Dosi and Orsenigo, 1988). This tension is supposed to increase when innovation activities are not based on incremental improvements of existing products, processes or services, but happen in a more radical way, fundamentally diverging from current business-as-usual. In addition, some characteristics associated with the futures innovative and entrepreneurial high growth ventures, such as being young, small are said to cause cause further information asymmetries between financiers and firms, making them likely to experience financial constraints when seeking external capital to fund innovative endeavors Revest et al. (2010).

While I later mostly discuss how networks among and between firms and investors might mitigate imperfect and asymmetric information, I here analyze first in isolation the interplay between external finance, firms' quality and quantity of innovation activities, and its structural and outcome characteristics. I thereby proposing that not a single but rather certain combinations of characteristics and context makes firms more likely to not find their financial needs met. The findings of this papers aim to broadly facilitate the research on the finance of technological change in later chapters by providing a theoretical and empirical foundation on generic issues of innovation finance. While important for research on technological change gin general, understanding the dynamics of finance, firm characteristics and types of innovation activities is of particular importance for understanding techno-economic transitions in large technological systems such as the energy sector, where progress in areas radically diverging from the current fossil-fuel based paradigms are needed.

Fig. B.1: Positioning the paper in the theoretical framework



The work on this paper start in the early period of my Ph.D. fellowship and was first presented on the "35^{th} DRUID Celebration Conference" 2013 in Barcelona, then on the "36^{th} ISBE Conference" 2013 in Cardiff, where was selected for the best paper award in the "Venture Capital, Finance and Taxation". It was furthermore presented at several internal and external research seminars, such as the Aalborg University workshop in academic writing and the SCANCOR seminar series in Stanford. Since it has been submitted to the Journal for "Industrial and Corporate Change", where it is currently under review.

1 Introduction

For many firms access to external financing represents a critical factor in determining a firm's ability to survive, grow, and engage in innovative activities (Beck and Demirguc-Kunt, 2006; Mina et al., 2013; Musso and Schiavo, 2008). Likewise, industry evolution and technological change requires adequate funding, and the structure and governance traditions of financial systems may impact the direction of industrial and technical change (Dosi, 1990; Mazzucato, 2013; Tylecote, 2007). A large proportion of firms do not demand external finance and of those who do a large proportion are able to raise the funds they need (Nightingale and Coad, 2014). Particularly such being young, small, and engaged in innovation and other activities characterized by uncertainty, are said to cause information asymmetries between financiers and finance seekers, making them less likely to raise the necessary external capital to fund innovation projects (Carreira and Silva, 2010; Freel, 2007; Hall, 2010).

We investigate how access to external financing for innovation activities is affected by firm-specific structural, behavioral and outcome characteristics. We propose that not a single but rather certain combinations of characteristics and context makes firms more likely to not find their financial needs met. We attempt to identify combinations of firm characteristics associated with potentially innovative ventures that lead to a disproportionate likelihood of credit rationing, while also taking into account the heterogeneity of financial needs. Moreover, in addition to incorporation the demand for finance and focus on combinations of potential characteristics, behavior and outcomes as potential explanations on financial constraints we differentiate our study from existing studies in that we use yearly, consistent innovation and finance surveys over a long time span (14 years). In this sense we contribute to a better understanding of the dynamics of the financing of entrepreneurship and innovation, an area that is generally under-researched (Hall, 2010; Hall and Lerner, 2009). Despite being generally under-researched, a number of earlier studies have investigated this problem area.

Traditionally, financial constraints are said to stem from asymmetric and imperfect information leading to a high perceived uncertainty and the need for banks and other financiers to gather firm-specific soft and private information for a proper assessment of creditworthiness (Berger et al., 2001; Carpenter and Petersen, 2002; Hall, 2010; Stiglitz and Weiss, 1981). Because of the difficulties associated with such assessments, financiers employ different strategies in their screening procedures. Such strategies include repeated contracts and relationship banking, specialization, monitoring and independent auditing and screening, milestone financing, and collateral. However, not only are these measures costly to the financier, they are also insufficient to reveal all relevant information or compensate for what remains unknown. Financiers are therefore particularly skeptical at the outset of the financing process when assessing proposals from firms that either have characteristics that amplify information asymmetry or are historically associated with high default risk. As a result, firms with a certain set of characteristics appear to be consistently penalized by capital markets, namely those that are young, small, and engaged in innovation activities with uncertain outcomes (e.g. Beck and Demirguc-Kunt, 2006; Canepa and Stoneman, 2008; Canton et al., 2013; Colombo and Grilli, 2007; Giudici and Paleari, 2000).

Using a 2-stage heckman probit model accounting for the heterogeneous need for external finance, we test hypotheses derived from the literature regarding the impact of firms structural, behavioral and outcome characteristics on capital access. We use a unique firm-level dataset composed of longitudinal survey data coupled with performance indicators, allowing us to incorporate micro-level firm characteristics. While the vast majority of existing studies rely on cross-sectional data, our panel data structure also allows us to control for contextual time-variant factors, such as the impact of business cycles. The data comprise a yearly survey of innovation activities and financial constraints that covers 14 years, from 2000 through 2013, with consistent question structure on both demand and supply of external financing. Compared to traditional innovation surveys (such as CIS), the data include more frequent rounds of surveying and a more detailed set of questions on finance.We find evidence that the effect of innovation on capital demand and supply is not uniform, but rather interdependent with other firm characteristics. Specifically, we find that the type of innovation is an important factor. While incremental innovation activities have little effect on the access to external finance, radical innovation activities tend to be penalized by capital markets. This appears to be particularly true for small innovators. We link these findings to how capital markets assess information flows.

The remainder of the paper is structured as follows. In section 2, we first survey the existing literature with respect to earlier, general studies of financial constraints, and derive a set of testable hypotheses on the interplay of innovation intensity, other firm characteristics and contextual factors.. The empirical strategy, data, and variables are presented and explained in section 3. Section 4 reports and discusses the results, followed by a conclusion in section 5.

2 Financial Constraints - Theory and Hypotheses

2.1 Innovation, information asymmetries, and financial constraints

Investments in innovation - mostly associated with R&D expenditures - appear to embody certain characteristics making them substantially different from other investments in several respects (Hall, 2010; Hall and Lerner, 2009). From a financier perspective, investing in radically innovative firms vis-á-vis their not or only moderately innovative counterparts, is foremost associated with higher information asymmetries between firm and financier, and related with higher risk and uncertainty (Dosi and Orsenigo, 1988) of investment outcomes.

Asymmetric information has been long recognized as a generic source of market failure in buyer-seller (Akerlof, 1970) commodity markets as well investor-investee (Myers and Majluf, 1984) capital markets. Such information asymmetries can be assumed to increase with rate and radicalness of the firm's innovation activities. This is because the information required to correctly assess innovative ventures is usually (i) private, and thus only given voluntarily (Moro et al., 2014) since firms may fear misuse and be reluctant to share it (Anton and Yao, 2002); (ii) complex, thus requiring in-depth knowledge regarding applied technologies or market circumstances; (iii) to a large extent tacit, thus requiring spatial proximity and face-to-face contact with financiers in order to be transferred (Arrow, 1962; Von Hippel, 1994); and (iv) innovation processes are reliant upon and embedded in human capital, which is often volatile and not easily maintained in the firm. The intangible nature of many innovation processes, and the fact that they have long time lags from initiation to returns, means that financiers are faced with projects for which they have little possibility of estimating the returns, as well as poor options to cover the risk by way of collateral.

Due to these informational deficiencies, and their often weaker balance sheets and frequent lack of fixed assets that could act as collateral, innovative firms are said to have a greater need to communicate their merits to financiers. The means of doing this vary greatly. In the literature on relationship banking (e.g. Berger and Udell, 2002), it is argued that repetitive communication and transactions lead to the building of trust, which in turn facilitates smooth communication and reduces both information asymmetries and the likelihood of moral hazard. An emerging literature on financial signaling focuses on the patenting behavior of firms as a mean of overcoming these informational barriers (Harhoff, 2011; Häussler et al., 2014), especially in the early stage of development (Hoenen et al., 2014).

The proposition that innovative firms are somewhat more likely to face financial constraints is supported by a growing body of empirical evidence. Westhead and Storey (1997) identify the most technologically sophisticated firms as much more likely to report that continual financial constraints had impeded firm growth. Czarnitzki and Hottenrott (2011) report similar findings especially for small R&D intensive firms. Freel (1999) identifies innovating firms as more likely to seek but less likely to obtain bank loans. Later, Freel (2007) added to earlier results, clarifying that even though a little innovation seems to be a good thing, more intensively innovating and small firms appear to be less successful in obtaining external financing.

The majority of studies have used firms in R&D-intensive industries, patenting firms, or the simple separation of firms into innovative and non-innovative categories as proxies for innovation. For example, Hall (2010) argues that using R&D as a proxy for innovation is justified because it makes up a major portion of innovation expenditures in firms in CIS-like surveys. However, despite the fact that R&D expenditures are a substantial part of innovation expenditures, only a minority of innovating firms has any R&D at all. Many of the changes in products, processes, and services are incremental, new-to-firm innovation. Consequently, it is important to recognize that innovation is ubiquitous and depends often on modes of doing and using technologies rather than being based on science or R&D (Jensen et al., 2007). Similarly, it is likely that these problems are exacerbated by the innovation intensity of firms, rather than being dependent on whether firms are innovative or not. This is easily seen if the perspective of the financier is taken: in a mediocre innovative firm where innovation activities make up a small share of turnover, the information asymmetries and uncertainty related to innovation will not pose substantial difficulties in assessment of creditworthiness. This changes when investing in firms generating a major share of their turnover with outcomes of recent innovation projects. It can be concluded that the relationship between innovation and financial constraints might be more nuanced than commonly depicted (Bellucci et al., 2014), particularly with respect to the intensity and type of innovation activities, and the combination with other firm characteristics. From this discussion we derive that we should not approach the analysis of innovation as innovation or not, rather the innovation intensity is likely to impact financial constraints. Moreover, the radical innovation projects involve additional asymmetries of information and time-lags between investments and outcome, again meaning a higher likelihood of financial constraints.

Hypothesis 1

a: Firms with a higher innovation intensity show a higher probability of being financially constrained.

b: This effect is more pronounced for firms engaged in radical vis-á-vis incremental innovation activity

2.2 Structural Characteristics: Innovation and the Liability of Newness and Smallness

Though it is often highlighted as a major barrier to business development (Bottazzi et al., 2014; Musso and Schiavo, 2008), the mere existence as well as economic significance of credit rationing, and so-called debt gaps for SMEs, is also contested (Berger and Udell, 2003; Cressy, 2012; Levenson and Willard, 2000). However, literature stemming from the strand of SME finance consistently identifies two characteristics of firms as being associated with asymmetric information, and consequently more financial constraints: being (ii) young or (iii) small. Reasons put forward are among others the liabilities of newness and size limitations, asymmetric information, agency problems, and the high, fixed costs of screening and monitoring such firms when compared to the potential profit for the financing institution (Beck and Demirguc-Kunt, 2006; Canepa and Stoneman, 2008; Carreira and Silva, 2010; Fazzari et al., 1988; Murray, 1999).

As illustrated above, in the case of innovation-intense firms, traditional investors with only a limited understanding of firms' processes, products, and markets face huge difficulties in assessing the quality of their innovation processes without undertaking substantial efforts in gathering tacit information. Until this point, we assumed the financier to be in need of understanding the very essence of the firm's innovation activities. However, traditional financiers such as banks, representing the major source of external capital to firms, also rely to a high degree on the available factual, or "hard", information, such as a firm's financial history, capital structure, and available collateral, when assessing creditworthiness. By doing so, they leave the selection of opaque innovation projects to the firm, if the firm fulfills other requirements based on hard information. In this sense, hard and soft information regarding the firm can serve as imperfect substitutes for an assessment of creditworthiness without directly taking the nature of its innovation projects into account. Yet, in the case of small and/or young firms, which tend to be more opaque to financiers (Berger et al., 2001), salient hard information such as rated debt, certified financial statements, annual reports, and other forms of codified signals and track records are often not available (Uzzi, 1999; Uzzi and Lancaster, 2003). In the absence of both hard and soft information, firms may face substantial obstacles in obtaining external financing, especially for their innovation projects. Consequently, we expect the effects of size, age, and the frequency of innovation projects to interact in a multiplicative rather than additive way, thus more than proportionally worsening a firm's access to external financing.

Hypothesis 2

a: Firms that are young and innovative show a disproportionally high probability of being financially constrained.

b: Firms that are small and innovative show a disproportional high probability of being financially constrained.

c: Both the effect of newness and smallness are more pronounced for firms engaged in radical vis-à-vis incremental innovation activity

2.3 Outcome: Innovation, Performance and Expectations

Whether a firm obtains external financing or not could in a world with perfect information be a simple function of self-assessed economic performance. In the absence of information asymmetries, a firm's expectation regarding its future financial performance is a perfect forecast and coincident with the banks assessment. However, in a real world asymmetric information and moral hazard drive a wedge between the borrowers and lenders ability to assess creditworthiness, and thus between supply and demand for external capital. Assuming the firm to be in possession of the most complete information set available to evaluate the performance of its innovation projects (Kon and Storey, 2003; Stiglitz and Weiss, 1981), the own projection of current and future financial performance should still serves as suitable approximation for its creditworthiness.

As a major source of information asymmetries, we expect a firms' innovation intensity to increase the wedge between a firm's self-assessed current and future financial performance and the access to external finance. We expect this to be particularly true for the case of positive performance projections, which are only partially received by the financier and lead to a situation of capital undersupply, as illustrated in the Stiglitz and Weiss (1981) model. However, this might also work the other way. Since this information is discounted by financiers and determines the lending decision and its conditions, firms have an incentive to act opportunistically and find ways to bias financiers in their favor, such as overstating progress in new product development or concealing critical strategic or technical details. This would lead to a situation such as the one depicted in the (De Meza and Webb, 1987) model, in which financiers arbitrarily provide credit to good and bad borrowers and lead to an oversupply of capital. It could be argued that financiers are primarily concerned with the financial performance of their portfolio firms. However, information on this is not easily available to the financier *ex ante*. We therefore posit that:

Hypothesis 3

a: A firms' current and projected economic performance influences their likelihood to meet financial constraints.

b: The relationship between economic performance and financial constraints is weaker in firms with higher innovation intensity.

Performance is here seen as how firms report their short-term profit expectations. A major merit of operationalizing financial performance according to the firm's own perceptions and expectations is that, in the case of innovative firms, this fully captures all their knowledge and their belief in the profitability of their innovation project, which cannot be captured by ex-post financial statements due to endogeneity issues. Innovation intensity is operationalized as firms' number of innovations which are new to the market as opposed to innovations only new to the firm (see also section 3 on variable description).

3 Econometric Modeling of Credit Demand and Supply

3.1 Data sources and context

Our primary data come from surveys of the management teams of a representative panel of private firms with at least five employees in North Jutland, Denmark. Respondents were interviewed[1] about their views of the past and

[1] In 1999–2010, data were collected through telephone interviews, whereas they were thereafter collected by means of a web-based questionnaire. This change has affected response rates negatively while not necessarily affecting representativeness to the same degree.

future development of variables like production, employment, profit, innovation activities, and access to financial capital. To ensure a shared understanding, the questions on innovation were posed only to a sub-sample of the population of private sector firms, such as those in the manufacturing industry and business services. The phrasing of the questions largely followed the form in which Community Innovation Surveys (CIS) pose questions on innovation and finance (e.g. Canepa and Stoneman, 2008; Pellegrino and Savona, 2013), making the results comparable to studies based on CIS data. The data are not fully representative of the total private business sector in the region, but within the sectors, there is a good match between the realized sample and the population of firms. Due to the focus of the survey, we only included firms reporting that they currently engage in innovation activities or plan to do so in the future.

Our case region is located in the north of Denmark, which is characterized as a peripheral area. This is illustrated by the fact that it has been an EU support Objective 2 area for years. There is one urban center, Aalborg, and the industry structure is somewhat different within the region, with the majority of R&D-based firms being in the Aalborg area. The total population in the region is around 600,000. One previous study on financial constraints in this region (Christensen, 2007) resembles our study; however, it was focused on a pre-crisis period and did not incorporate all constraints and statistical controls.

3.2 Variable description

The following subsection briefly describes the variables utilized in the empirical analysis and gives suggestions regarding their impact. An exhaustive description of all variables can be found in table **??**.

Dependent Variables

Our main dependent variable of interest (*constraints*) is dichotomous and derived from the survey answers whether the firm experienced constraints in raising external capital to finance innovation projects in the corresponding period (0:No, 1:Yes). Adittionally, in our selection model we consider a variable (*demand finance*) represents the firms' general need for external capital to finance innovation projects. On a five-point Likert scale, firms where asked to rate the importance of external finance for their innovation activities (5: very high, 4: high, 3: medium, 2: low, 1: very low/none). We transformed it in a dichotomous variable taking the value of one for firms that report external finance to have at least some importance. We employ this variable in the first step of our analyses to take into account endogenous selection of firms seeking external finance Mina et al. (2013).

Independent variables

Behavioral variables: Innovation intensity In the survey, firms list whether they have introduced new products, processes, or services that are either new only to the firm (*incremental innovations*) or to the market/world (*radical innovations*)[2] and if, how many. Since incremental innovations are in contrast to radical innovations already to some extend known to the market, we associate them with less uncertainty and a greater capacity to be understood by the financier. As such, they are expected show a somewhat smaller effect on the firm's access to external financing.

However, we do not posit a linear relationship of *innovation intensity* and the following structural variables (*size, age*) and the likelihood of facing financial constraints, but rather one with decreasing marginal effects. Once a firm develops a track record for a number of years, asymmetric information problems stemming from a lack of historical data are likely to be alleviated, and further benefits from aging only manifest in possible reputational effects and increasing strength of the financier-firm relationship. We suggest the same pattern for size, where at a certain size legal disclosure requirements and the establishment of professional finance and accounting management eliminate a substantial share of information asymmetries. While innovation is considered as a source of information asymmetries, we also expect this effect to soften with increasing innovation intensity. Firms that frequently engage in a high number of innovation projects are likely to develop routines to manage this process in a more structured way, which may be associated with increasing documentation and therefore higher transparency. Therefore, the variables incremental and radical innovation intensity are used in all models as the logarithmic transformation of the number of new products, processes, or services introduced in the corresponding observation period.

Structural characteristics: Firm size and age We include the firm specific structural characteristics most commonly associated with financial constraints, *size* (in number of employees) and *age* (in years), and coined these two variables respectively the liability of newness and liability of smallness.

[2] This distinction is in line with what is commonly used in innovation studies using CIS surveys.

As discussed above, to account for assumed decreasing marginal impact as well as the skewedness of the variables distribution, size and age enter the model in their natural logarithm.

Outcome: Perceived current and future performance Firms were asked about the development of their realized profits in the current period (increased, same, decreased). A reported realized increase in profits in the observation period obviously represents a positive signal for financiers, which should decrease the firm's likelihood of being financially constrained, and *vice versa*.[3] We code this question in two dummy variables, first $real\ result\ +$ indicating positive, and $real\ result\ -$ indicating negative self-reported results in the current period. We introduce a dynamic perspective on external innovation finance by way of also incorporating the firm's self-reported expected future performance of the firm. Here, we utilized another question, where firms reported their predicted development of profits for the next period (increase, same, decrease), which we also code in two dummy variables, indicating positive ($exp\ result\ +$) and negative ($exp\ result\ -$) profit expectations. Assuming the firms to have the most complete set of information to make prediction regarding their future performance, in absence of information asymmetries we associated positive profit expectation with less financial constraints.

Conditions for innovation We further utilized the answers to additional questions on general opinions and impressions of the firm that might provide insights regarding the type of innovation likely to be produced. *Imp. tech* represents a dummy variable taking a value of one if the firm believes that technological knowledge is of high or highest importance to its business (on a five-point Likert scale), indicating that the firm is technology based. *Imp. IPR* relates to the firm's assessment of the importance of intellectual property protection, and is an indicator for more technology-based firms operating in an environment where innovation outcomes can be codified and protected. Finally, *Imp. market* is about the belief that market knowledge is vital for the firm, indicating competitive, complex, and changing market conditions.

Control variables

[3]However, this only holds true for the minimum level of documentation and accounting transparency that enables a firm to convincingly prove its credibility to external financiers.

The region: First, the firm's environment is assumed to influence its access to external financing. Denmark's North Jutland region can be categorized as a fairly peripheral one. Modern instruments of innovation finance such as private equity and venture capital are scarcer there, which leaves debt as the predominant form of external innovation finance. Since the assessment of small, young, and innovative firms can be facilitated by tacit knowledge exchange and social proximity, we expect firms in regions outside the Aalborg region, North Jutland's urban core, to be more likely to face financial constraints. Therefore, in some models we also include further dummy variables indicating the firm is located in the inner Aalborg metropolitan region (*region 1*), or the larger, relatively less densely (but compared with the rest of northern Jutland still high) populated region around Aalborg (*region 2*).

The industry: Firms in the manufacturing industry usually embody a higher share of tangible assets suitable to serve as collateral, and thus are favored by asset-based creditability evaluation techniques. Furthermore, production processes and their output may be better understood and valued than the somewhat intangible work of service firms. Therefore we suggest firms in the manufacturing industry to be less likely to face financial constraints.

Ownership structure and legal form: We also expect the firm's ownership structure to matter. If it is a *subsidiary*, it may be nurtured by its parent company, and thus be less in need of external financing. Additionally, it may draw on the reputation and credibility of its parent company, which eases the way to obtaining external financing. The firms' *legal form* makes them likely to differ in demand and access to external capital. Publicly traded companies obviously finance themselves on public capital markets for the most part and therefore have less demand for other sources of external financing than firms of other legal forms. Among privately owned businesses, we assume limited liability firms to be more likely to experience financial constraints than sole proprietorship, in which the firm's credit is backed by the private wealth of the entrepreneur.

3.3 Data Analysis and Descriptive Statistics

The refined data set represents an unbalanced panel containing 8,447 observations of 2,723 unique firms. Only a subpopulation of firms was asked to answer the set of innovation and financial constraints-related questions relevant for this study, which leaves us with 2,822 observations of 1,169 unique firms, whose participation in the different survey waves ranges from 1 to 12, where about 25% of firms participated in 2 or fewer and 95% in 7 or fewer waves. The participation by wave ranges from 135 in 2013 to a peak of 316 in 2010. The distribution of firms over years, regions, and industries can be found in table B.5 in the appendix.

Table B.1: Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min.	Max.
		Dependent Variables			
need finance	2,822	0.63	0.48	0	1
constraints	2,093	0.17	0.38	0	1
		Independent Variables			
$size_{count}{}^*$	2,822	49.78	95.79	1	1600
$age_{count}{}^*$	2,822	17.66	12.68	1	135
planned inno	2,822	0.68	0.47	0	1
inc. $inno_{count}{}^*$	2,822	4.06	10.6	0	100
rad $inno_{count}{}^*$	2,822	1.59	6.3	0	99
imp. tech	2,822	0.09	0.29	0	1
imp. ipr	2,822	0.09	0.29	0	1
imp. market	2,822	0.23	0.42	0	1
real result +	2,822	0.39	0.49	0	1
real result -	2,822	0.23	0.42	0	1
exp result +	2,822	0.39	0.49	0	1
exp result -	2,822	0.16	0.37	0	1
		Control Variables			
region 1	2,822	0.40	0.49	0	1
region 2	2,822	0.58	0.49	0	1
firm subsidiary	2,822	0.23	0.45	0	1

*: For the sake of clarity, firm size (employees),age (years), incremental and radical innovation intensity (innovation count) in full number and not in logarithmic transformation.

Table B.1 provides some descriptive statistics at the firm level through the different waves. 63% of the firms in our sample express the need for external finance at all, while the others prefer to finance innovation projects by internal means. 17% report that they experienced financial constraints in external innovation finance in the corresponding observation period, which is about a quarter of firms expressing financial needs. This result roughly match with comparable studies. The average firm has slightly fewer than 50 employees and an age of about 17 years, where both characteristics skew high and positive. Over 40% report that they introduced at least one product, process, or service new to the firm in the corresponding period, while a slightly higher percentage introduced innovations new to the industry and the market, and roughly 70% planned to start new innovation projects in the next year, what sums up to an average of 4.06 incremental and 1.59 radical innovations per firm and year . About a quarter of the firms consider knowledge on market conditions as crucial to their success, whereas only 9% think so regarding technological knowledge and IPR.

tarble B.5 in the appendix provides a breakdown of the firms need for finance, experienced financial constraints, and incremental and radical innovation activity by year, region and industry. Financial constraints show to peak in the years 2003 and 2009, when (related) demand for external finance for innovation projects is also at it's high as is the average intensity of radical innovation . The manufacturing industry appears to be the most innovative and therefore has also the highest demand for innovation finance. The results of a bivariate analysis, presented in a pairwise correlation matrix in Table 3, provide the first insights into the general interplay among innovation intensity, the need for financing, and credit constraints.

Table B.2: Correlation Matrix

		(1) need finance	(2) constraints	(3) region_2	(4) size	(5) age	(6) subsidiary	(7) inno inc
(1)	constraints	0.451*						
(2)	region 2	-0.065*	-0.060*					
(3)	size	-0.080*	-0.106*	-0.044*				
(4)	age	-0.062*	-0.054*	-0.037	0.230*			
(5)	subsidiary	-0.108*	-0.0779*	0.023	0.045*	0.076*		
(6)	inno inc	0.008	-0.007	0.026	0.194*	0.051*	0.013	
(7)	inno rad	-0.006	0.037	0.020	0.060*	-0.031	-0.038	0.430*
(8)	imp tech	0.007	-0.015	0.028	0.006	0.008	0.017	-0.004
(9)	imp ipr	0.033	-0.002	0.033	-0.003	-0.070*	-0.039	0.060*
(10)	imp market	0.012	-0.034	0.015	0.054*	0.012	-0.002	0.072*
(11)	real result +	-0.065*	-0.042*	0.055*	0.008	0.004	-0.045*	0.031
(12)	real result -	0.060*	0.075*	-0.055*	0.000	-0.008	-0.014	0.039
(13)	exp result +	0.035	0.039	0.072*	-0.027	-0.099*	-0.017	0.094*
(14)	exp result -	0.008	0.010	-0.047*	-0.020	0.031	-0.037	-0.030
		(8) inno rad	**(9) imp tech**	**(10) imp ipr**	**(11) imp market**	**(12) real result +**	**(13) real result -**	**(14) exp result +**
(8)	imp tech	0.005						
(9)	imp ipr	0.105*	0.142*					
(10)	imp market	0.049*	0.114*	0.251*				
(11)	real result +	0.053*	0.011	0.012	0.017			
(12)	real result -	0.005	0.015	-0.015	0.003	-0.430*		
(13)	exp result +	0.097*	0.017	0.025	0.028	0.115*	0.116*	
(14)	exp result -	-0.033	-0.015	-0.040	-0.013	-0.020	0.129*	-0.341*

*: $p < 0.01$, two-tailed Pearson correlation

As expected, both age and size are negatively correlated with the need for external finance as well as with financial constraints. Surprisingly, neither the intensity of incremental nor of radical innovation shows non-negligible correlation coefficients in magnitude or significance. This is in line with (Christensen, 2007), who in a bivariate setting found no evidence that innovative firms are particularly affected by financial constraints. No strong correlation indicating collinearity can be found.

3.4 Model Setup and Empirical Strategy

Our data set represents an unbalanced panel, where roughly half of the firms participated in one wave and the other half in two to twelve, regressively developing. Since the methods available for unbalanced panel data regressions with selection and dichotomous dependent variables are very limited, we instead choose to use pooled data and include year dummies to capture year effects. To address the issue of serial correlation among multiple observations of the same firm, we relax the assumption that standard errors are independently and identically distributed by clustering them at the firm level, which allows for within-group correlation. Furthermore, we used multivariate imputation techniques in the rare cases of missing data on firm characteristics and survey question replies of the independent variables, where for every single variable less then 5% of observations show missing cases.

The dichotomous nature of our dependent variable and the very nature of our survey data suggest the use of a probit model. To analyze the interplay between supply and demand for external financing for innovation, we chose a two-stage model with endogenous selection, which allowed us to construct a consistent model for decisions both to seek and to obtain financing for innovation projects, where the former obviously represents the prerequisite for the latter. This is done with a technique equivalent to the well-established two-stage Heckman correction in linear models (Heckman, 1979), applied for bivariate probit models (Van de Ven and Van Praag, 1981) and estimating a firm's likelihood to experience financial constraints by full maximum likelihood.

We execute our econometric analysis as follows. Model one includes control variables for the corresponding year, the firm's industry affiliation and its legal form, some basic firm characteristics, its incremental and radical innovation intensity (hypothesis 1 a and b), and its perceived importance of some factors associated with innovation. In model two, we add an interaction term between the firms' incremental innovation intensity and its structural characteristics size and age (*inc. inno*size*^{ref}, *inc. inno*age*^{ref}). To test the interplay between innovation intensity and the liability of newness and smallness, we reverse the magnitude of both age and size to have high values for young and small firms, and *vice versa*. We do the same in model three for radical innovation intensity (*rad. inno*size*^{ref}, *rad. inno*age*^{ref}). In both models we test if young and small firms are over-proportionally affected by the assumed negative impact of innovation intensity on the access to external finance (hypothesis 2 a and b), and by their comparison if the type of innovation activity matters (hypothesis 2 c). Then in model four we add first the firms reported increase (*real result* +) or decrease (*real result* -) in profits in the current period, and in model five the firms expectation for the next period (exp result +, exp result -) to test the interplay between realized and perceived firm level outcomes and different forms of innovation intensity (hypothesis 3 a and b).

4 Results and Discussion

table B.6 reports the results of the probit models with endogenous selection (where the first stage is reported in **??** , testing for the likelihood that a firm experiences financial constraints in financing innovation projects conditional to its demand for external financing.

4.1 Demand for external innovation finance

In the first stage of the model to be found in table **??** in the appendix, we test the likelihood of having demand for external capital to finance innovation projects. Even though this stage is not of main interest for our analysis, it is necessary for endogeneity reasons and results may be interesting in themselves. Surprisingly, demand for external innovation finance appears at first glance to be quite inelastic to firm characteristics and innovation intensity, which holds true for incremental and radical innovation alike. Firms that are a subsidiary have a significantly lower demand for external finance, probably because they are likely to be supplied with funding by their parent company. The variable *region*2 (firms in the wider, less densely populated Aalborg area) has a negative sign and is significant in all models indicating that demand for external finance of innovation is not as widespread among firms in these regions as is the case in the inner urban area. Realized positive profits decreases the demand for external finance. This indicates that, in line with the pecking order theory (Myers and Majluf, 1984), firms indeed prefer to finance innovation activities with internal funds such as accumulated profits. Contrary to initial expectations, the firm's size and age have no significant effect on its demand for financing, which appears puzzling at first glance, since the majority of theories and evidence claim that small and young firms are in greater need of external financing. Overall, we see a somewhat limited explanatory power of traditional firm characteristics and innovation indicators alike for the financial needs of firms in our sample. It should, however, be reiterated that the bulk of the earlier literature has focused on the supply side rather than on demand. Yet, while appreciating the importance of considering the interplay between demand and supply of capital, our focus in this analysis lays on the constraints firms meet to their innovation financing.

4.2 Supply for external innovation finance

In the second stage, we test the firm's likelihood to experience financial constraints. In model one, we see that size matters to obtaining financing, as increasing size reduces the chances of being constrained, significant at least at a 5% level. In line with hypothesis 3a, radical innovation intensity is associated with a higher probability of being financially constrained, significant on 5% level. Yet, this holds not true for incremental innovation, which shows a negative but not significant coefficient, lending support to hypothesis 3b, and at the same time calling for more nuanced understanding of the relationship between different types of firm level innovation activities and financial constraints.

In model two, we introduce interaction terms with the structural characteristics age and size (reversed) and the behavioral variable, incremental innovation intensity ($inc.inno * size^{rev}, inc.inno * age^{rev}$). While the interaction with age shows no statistical significance (leading to a rejection of hypothesis 2a), the interaction with size (reversed) indeed shows a positive coefficient significant at the 5% level, indicating in favor of hypothesis 2b that high innovation intensity and smallness indeed amplify each others negative effect on access to external finance. The same holds true in model three for the interaction with radical innovation intensity. As speculated in hypothesis 2c, this effect appears to be higher in the case of radical innovation.

In model four we test for the additional effect of being a firm reporting to be a good or a bad performer, operationalized by positive or negative development of profits in the observation period. While good performance in this model leads to no benefits in accessing external finance, bad performance indeed appears to be penalized by capital markets. The coefficient for negative profit development shows significance at 10% level, lending partial and weak support to hypothesis 3a. However, while realized outcomes appear to at least slightly matter, we see no significant effect at all for the firms profit expectations introduced in model five. Interestingly, when including realized and expected outcome characteristics, in both model four and five the coef-

Table B.3: Regression table – Probit model with endogenous selection. Dependent Variable: Financial Constraints

	I			II			III			IV			V		
	Coeff.	SE	AME	Coeff.	SE	AME	Coeff.	SE	AME	Coeff.	SE	AME	Coeff.	SE	AME
region 1	0.018	(0.119)	0.008	0.005	(0.119)	0.010	0.027	(0.116)	0.030	0.015	(0.095)	-0.054	0.014	(0.115)	-0.018
region 2	-0.157	(0.134)	-0.056	-0.155	(0.131)	-0.061	-0.145	(0.131)	-0.072	-0.186*	(0.094)	-0.024	-0.195	(0.118)	-0.047
size	-1.326**	(0.467)	-0.466	-5.457***	(1.456)	-0.406	-6.728**	(2.104)	-0.464	-1.248***	(0.293)	-0.391	-1.397***	(0.355)	-0.446
age	0.038	(0.362)	0.011	0.024	(1.263)	0.041	-0.454	(1.932)	0.019	-0.181	(0.263)	-0.039	-0.024	(0.347)	0.005
subdidiary	-0.146	(0.174)	-0.053	-0.133	(0.158)	-0.054	-0.083	(0.154)	-0.052	-0.265***	(0.080)	-0.053	-0.214	(0.134)	-0.052
imp tech	-0.126	(0.146)	-0.043	-0.130	(0.145)	-0.044	-0.134	(0.142)	-0.046	-0.0611	(0.119)	-0.036	-0.113	(0.146)	-0.043
imp ipr	-0.086	(0.152)	-0.029	-0.069	(0.151)	-0.020	-0.080	(0.147)	-0.020	-0.001	(0.123)	-0.025	-0.052	(0.151)	-0.028
imp market	-0.182	(0.101)	-0.063	-0.178	(0.101)	-0.061	-0.171	(0.100)	-0.061	-0.120	(0.083)	-0.061	-0.168	(0.106)	-0.061
inno inc	-0.192	(0.265)	-0.064	2.262*	(1.085)	0.787	-0.171	(0.245)	-0.044	0.011	(0.196)	-0.040	-0.147	(0.269)	-0.071
inno rad	1.022**	(0.345)	0.352	1.190***	(0.342)	0.402	4.227**	(1.501)	1.483	0.627*	(0.268)	0.407	0.888*	(0.422)	0.351
inno inc*age^{rev}				0.138	(1.537)										
inno inc*size^{rev}				5.475**	(1.759)										
inno rad*age^{rev}							0.616	(2.140)							
inno rad*size^{rev}							6.307**	(2.273)							
real result +										-0.051	(0.077)	0.002			
real result -										0.189*	(0.086)	0.082			
exp result +													0.138	(0.091)	0.035
real result -													0.075	(0.115)	0.022
Year controls	Yes			Yes						Yes			Yes		
Industry controls	Yes			Yes						Yes			Yes		
Legal controls	Yes			Yes						Yes			Yes		
athrho	-0.040	0.748		-0.134	0.606		0.575	-0.600		4.623	60.858		0.803	0.520	
rho	-0.040	0.747		-0.133	0.595		-0.329	0.512		0.999	0.023		0.391	0.680	
N stage 1	2,093			2,093			2,093			2,093			2,093		
N stage 2	1,061			1,061			1,061			1,061			1,061		
Wald chi2	48.160			53.300			47.460			82.680			61.520		
Prob > chi2	0.010			0.006			0.022			0.000			0.001		
log-likelyhood	-2050			-2,045			-2,046			-2,047			-2,049		

*, **, *** indicate significance at 10, 5, 1 percent level

ficient as well as significance of radical innovation intensity decreases. This might indicate a more nuanced relationship between innovation activity and outcome related to technology.

4.3 Robustness tests

To evaluate the robustness of our findings, we carried out additional robustness tests. First, we ran only the supply model (stage 2) in a fixed effects probit model. For our structural and innovation variables, we also tried different transformations (other than the here applied logarithmic one) such as the squareroot, and also the non-transformed terms. For our outcome variable, we also replaced the self reported profits by balance sheet data from Danish register data (which is unfortunately only available for a subset of firms). While mostly not as pronounced, all results point in a similar direction. The period we analyze span across the financial crisis and it can be presumed that this has an effect on conditions for obtaining external finance (Cowling et al., 2012; Vermoesen et al., 2009). In our empirical analyses we included year dummies to capture potential effects from changes in business cycles but additionally we introduced a number of macroeconomic business cycle indicators but found no effect from this.

5 Conclusion

Our approach in this study was to build on previous theories and studies on demand and constraints for financing for different types of firms and to add new, improved ways of analyzing this problem area. Our hypotheses were built to render a more nuanced picture of the financial constraints problem than has been presented to date. We were able to analyze this problem area from a longitudinal perspective, and although our overall results are in contrast to some previous findings in the literature we did find new insights that contribute an additional understanding of financial constraints.

It has been claimed that by and large firms who apply for credit gets it (Nightingale and Coad, 2014) but that some types of firms may be financially constrained. Regarding the demand side our results indicate weak systematic patterns in which types of firms are demanding external finance. Unsurprisingly, the realized, positive economic results decreases demand for external finance as does the firms' status as subsidiary. The main, second stage analyses showed that the effect of innovation per se on capital demand and supply is not uniform, but rather interdependent on other firm characteristics. We furthermore find the type of innovation to matter. While incremental innovation is rewarded by financiers, the results for more radical or technology-based innovations are more ambiguous.

It is likely that in a small and dense region, where innovation activities are primarily incremental and not science-based, financiers are better able to cope with asymmetries of information and other reasons for credit rationing. Hence, static, non-innovative firms are, in our analyses, financially constrained, while firms with some innovation are rewarded, and technology-based, high-tech innovation firms are constrained. This is congruent with some earlier studies that posit that "some, not too much, innovation is good" (Freel, 2000, 2007).

Our findings lead us to question the generalization of existing theories in the field. Whereas financial markets are often seen as prime examples of full information and extended mobility of production factors, our results indicate that the demand and supply of the finance nexus is nuanced and highly contextual. As mentioned, another, complementary interpretation is that capital markets work differently in small, dense environments because information flows more easily and networks of firms and of financiers facilitate both mitigating information asymmetries and the insourcing of knowledge on capital market reactions (Sorenson and Stuart, 2001). This is consistent with (Bellucci et al., 2014) who find that when financiers have well-established lending relationships with firms, they evaluate innovation positively, whereas the innovation variable has a negative impact on access to credit for firms that are more likely to suffer from information asymmetries. Proximity is, in turn, a facilitator of reducing asymmetric information, hence increasing access to financing. It is likely that the regional context is a powerful explanation as to why existing theories do not seem to fit our case. This does not disprove these established theories, but points to the need to take contextual factors into account and to evaluate these theories differently in different regional settings.

The findings not only complicate the theoretical understanding of access to financing, but may also have policy implications. Most public support programs for access to financing place restrictions on eligibility; most often their financing is available only to firms that are young, small, innovative, or some combination thereof, at least in some regions. The results of our study indicate a need for careful consideration of these criteria.

A number of limitations apply to how far we can go in drawing universally valid conclusions. The study was confined to a small region in a small country. As we have argued, entrepreneurial finance is to a large extent contextual (Ning et al., 2015), and the results may have been different in another financial system. We also treated financiers and types of financing as if they were homogeneous. In reality, there are vast differences between, for example, venture capital and bank financing, and different results might be seen if the analyses were confined to only one type of capital (Brown et al., 2012).

For further research, we suggest continuing to explore the impact of innovation types on financial constraints. For example, the latest round of CIS-survey results show that North Jutland has now moved up from the bottom of the rankings to become the most innovative region in Denmark, despite still being the one with the lowest rate of R&D activities. Furthermore, these survey results show that the major difference between other regions and North Jutland is that the latter's firms have been engaged in organizational change to a larger extent. The capital markets may view such innovations particularly positively.

References

Akerlof, G. A. (1970). The market for lemons: Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3):488–500.

Anton, J. and Yao, D. (2002). The sale of ideas: Strategic disclosure, property rights, and contracting. *Review of Economic Studies*, 69(3):513–531.

Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Eeconomic Studies*, 29(3):155–173.

Beck, T. and Demirguc-Kunt, A. (2006). Small and medium-size enterprises: Access to finance as a growth constraint. *Journal of Banking & Finance*, 30(11):2931–2943.

Bellucci, A., Favaretto, I., and Giombini, G. (2014). Does innovation affect credit access? new empirical evidence from italian small business lending. *IAW Discussion Papers, no.104*.

Berger, A., Klapper, L., and Udell, G. (2001). The ability of banks to lend to informationally opaque small businesses. *Journal of Banking & Finance*, 25(12):2127–2167.

Berger, A. and Udell, G. (2002). Small business credit availability and relationship lending: The importance of bank organisational structure. *The Economic Journal*, 112(477):F32–F53.

Berger, A. N. and Udell, G. F. (2003). Small business and debt finance. In Acs, Z. J. and Audretsch, D. B., editors, *Haandbook of Entrepreneurship*, pages 299–328. Dordrecht: Kluwer.

Bottazzi, G., Secchi, A., and Tamagni, F. (2014). Financial constraints and firm dynamics. *Small Business Economics*, 42(1):99–116.

Brown, J. R., Martinsson, G., and Petersen, B. C. (2012). Do financing constraints matter for r&d? *European Economic Review*, 56(8):1512–1529.

Canepa, A. and Stoneman, P. (2008). Financial constraints to innovation in the uk: evidence from cis2 and cis3. *Oxford Economic Papers*, 60(4):711–730.

Canton, E., Grilo, I., Monteagudo, J., and Van der Zwan, P. (2013). Perceived credit constraints in the european union. *Small Business Economics*, 41(3):701–715.

Carpenter, R. and Petersen, B. (2002). Capital market imperfections, high-tech investment, and new equity finance. *The Economic Journal*, 112(477):F54–F72.

Carreira, C. and Silva, F. (2010). No deep packets: Some stylized empirical results on firms? *Journal of Economic Surveys*, 24(4):731–753.

Christensen, J. (2007). Constraints on innovation finance in north jutland, Denmark. *European Planning Studies*, 15(9):1163–1180.

Colombo, M. and Grilli, L. (2007). Funding gaps? access to bank loans by high-tech start-ups. *Small Business Economics*, 29(1):25–46.

Cowling, M., Liu, W., and Ledger, A. (2012). Small business financing in the uk before and during the current financial crisis. *International Small Business Journal*.

Cressy, R. (2012). Funding gaps. *The Oxford Handbook of Entrepreneurial Finance*, page 255.

Czarnitzki, D. and Hottenrott, H. (2011). R&d investment and financing constraints of small and medium-sized firms. *Small Business Economics*, 36(1):65–83.

De Meza, D. and Webb, D. (1987). Too much investment: a problem of asymmetric information. *The Quarterly Journal of Economics*, 102(2):281–292.

Dosi, G. (1990). Finance, innovation and industrial change. *Journal of Economic Behavior & Organization*, 13(3):299–319.

Dosi, G. and Orsenigo, L. (1988). Coordination and transformation: an overview of structures, behaviours and change in evolutionary environments. In Dosi, G., Freeman, C., Nelson, R., and Soete, L., editors, *Technical Change and Economic Theory*, pages 13–37, London. Pinter Publishers.

Fazzari, S., Hubbard, R. G., and Petersen, B. C. (1988). Financing constraints and corporate investment.

Freel, M. (1999). The financing of small firm product innovation within the uk. *Technovation*, 19(12):707–719.

Freel, M. (2000). Barriers to product innovation in small manufacturing firms. *International Small Business Journal*, 18(2):60–80.

Freel, M. (2007). Are small innovators credit rationed? *Small Business Economics*, 28(1):23–35.

Giudici, G. and Paleari, S. (2000). The provision of finance to innovation: a survey conducted among italian technology-based small firms. *Small Business Economics*, 14(1):37–53.

Hall, B. H. (2010). The financing of innovative firms. *Review of Economics and Institutions*, 1(1):1–30.

Hall, B. H. and Lerner, J. (2009). The financing of r&d and innovation. NBER Working Paper 15325.

Harhoff, D. (2011). *Handbook of research on innovation and entrepreneurship*, volume 55, chapter The role of patents and licenses in securing external finance for innovation. Edward Elgar Publishing.

Häussler, C., Harhoff, D., and Müller, E. (2014). How patents inform vc investors - the case of biotechnology. *Research Policy*, 43:1286–1298.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, pages 153–161.

Hoenen, S., Kolympiris, C., Schoenmakers, W., and Kalaitzandonakes, N. (2014). The diminishing signaling value of patents between early rounds of venture capital financing. *Research Policy*, 43(6):956–989.

Jensen, M. B., Johnson, B., Lorenz, E., and Lundvall, B. Å. (2007). Forms of knowledge and modes of innovation. *Research policy*, 36(5):680–693.

Kon, Y. and Storey, D. (2003). A theory of discouraged borrowers. *Small Business Economics*, 21(1):37–49.

Levenson, A. and Willard, K. (2000). Do firms get the financing they want? measuring credit rationing experienced by small businesses in the us. *Small Business Economics*, 14(2):83–94.

Mazzucato, M. (2013). Financing innovation: creative destruction vs. destructive creation. *Industrial and Corporate Change*, 22(4):851–867.

Mina, A., Lahr, H., and Hughes, A. (2013). The demand and supply of external finance for innovative firms. *Industrial and Corporate Change*, 22(4):869–901.

Moro, A., Fink, M., and Kautonen, T. (2014). How do banks assess entrepreneurial competence? the role of voluntary information disclosure. *International Small Business Journal*, 32(5):525–544.

Murray, G. (1999). Seed capital funds and the effect of scale economies. *Venture Capital: An International Journal of Entrepreneurial Finance*, 1(4):351–384.

Musso, P. and Schiavo, S. (2008). The impact of financial constraints on firm survival and growth. *Journal of Evolutionary Economics*, 18(2):135–149.

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2):187–221.

Nightingale, P. and Coad, A. (2014). Muppets and gazelles: political and methodological biases in entrepreneurship research. *Industrial and Corporate Change*, 23(1):113–143.

Ning, Y., Wang, W., and Yu, B. (2015). The driving forces of venture capital investments. *Small Business Economics*, 44(2):315–344.

Pellegrino, G. and Savona, M. (2013). Is money all? financing versus knowledge and demand constraints to innovation. Paper for 35th DRUID conference, Barcelona, Spain, june 17.-19.

Revest, V., Sapio, A., et al. (2010). Financing technology-based small firms in Europe: what do we know? *Small Business Economics*, pages 1–27.

Schumpeter, J. A. (1942). *Capitalism, Socialism and Democracy*. Harper, New York.

Sorenson, O. and Stuart, T. E. (2001). Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology*, 106(6):1546–88.

Stiglitz, J. and Weiss, A. (1981). Credit rationing in markets with incomplete information. *American Economic Review*, 71(3):393–410.

Tylecote, A. (2007). The role of finance and corporate governance in national systems of innovation. *Organization Studies*, 28(10):1461–1481.

Uzzi, B. (1999). Embeddedness in the making of financial capital: How social relations and networks benefit firms seeking financing. *American sociological review*, pages 481–505.

Uzzi, B. and Lancaster, R. (2003). Relational embeddedness and learning: The case of bank loan managers and their clients. *Management Science*, pages 383–399.

Van de Ven, W. P. and Van Praag, B. (1981). The demand for deductibles in private health insurance: A probit model with sample selection. *Journal of econometrics*, 17(2):229–252.

Vermoesen, V., Deloof, M., and Laveren, E. (2009). Long-term debt maturity and financing constraints of SMEs during the global financial crisis. *Small Business Economics*, pages 1–16.

Von Hippel, E. (1994). Sticky information and the locus of problem solving: Implications for innovation. *Management Science*, 40(4):429–439.

Westhead, P. and Storey, D. (1997). Financial constraints on the growth of high technology small firms in the United Kingdom. *Applied Financial Economics*, 7(2):197–201.

Appendix

Table B.4: Variable Descriptions

Variable	Type	Description
		Dependent Variables
demand finance	dichotomous	Firm in need for external finance
constraints	dichotomous	Firms experienced finance constraints
		Behavior: Innovation intensity
inc. inno	continuous	Firms number of introduced incremental innovation, natural logarithm: ln(1+x)
rad. Inno	continuous	Firms number of introduced radical innovation, natural logarithm: ln(1+x)
inno planned	dichotomous	Firm plans innovation in next period
		Structure
size	continuous	Firms employees, natural logarithm: ln(x)
age	continuous	Firms age in years, natural logarithm: ln(x)
		Outcome: Performance
real result +	dichotomous	Firms realized profits positive
real result −	dichotomous	Firms realized profits negative
exp result +	dichotomous	Firms expected profits positive
exp result −	dichotomous	Firms expected profits negative
		Behavior: Innovation intensity
imp. technology	dichotomous	Perception: High importance of access to technology
imp. IPR	dichotomous	Perception: High importance of IPR
imp. market	dichotomous	Perception: High importance of market knowledge
		Controls
region 1	dichotomous	Firm located in the central Aalborg region
region 2	dichotomous	Firm located in a metropolitan region
industry	dichotomous	Firm industry, (0) others, (1) manufacturing, (2) service, communication and finance
legal form	categorical	Firm legal form, (0) others, (1) public traded, (2) limited liability, (3) private
subsidiary	dichotomous	Firm is a subsidiary

Table B.5: Descriptive Statistics by Categories

Category	N	Percent	demand finance, mean	constraints, mean	inc. inno intensity, mean	rad. inno intensity, mean
Total	2822.00	100.00	0.63	0.17	4.06	1.59
Distribution and characteristics of firms by year						
2000	207.00	7.34	0.71	0.18	3.20	1.13
2001	200.00	7.09	0.74	0.16	4.45	2.24
2002	179.00	6.34	0.69	0.11	3.41	1.53
2003	188.00	6.66	0.76	0.21	5.80	2.90
2004	196.00	6.95	0.61	0.18	5.62	2.06
2005	187.00	6.63	0.66	0.13	4.57	1.32
2006	193.00	6.84	0.66	0.12	4.34	1.20
2007	179.00	6.34	0.67	0.12	4.18	1.46
2008	200.00	7.09	0.72	0.18	4.80	1.30
2009	260.00	9.21	0.76	0.25	7.44	3.71
2010	316.00	11.20	0.48	0.18	2.47	0.82
2011	212.00	7.51	0.48	0.16	1.89	0.69
2012	170.00	6.02	0.48	0.23	1.41	0.61
2013	135.00	4.78	0.48	0.15	2.69	0.83
Distribution and characteristics of firms by industry						
manufacturing	1442.00	51.10	0.68	0.17	4.73	1.89
service & finance	555.00	19.67	0.48	0.19	3.18	1.26
others	825.00	29.23	0.65	0.16	3.50	1.29

Note: incremental and radical innovation intensity (innovation count) in full number and not in logarithmic transformation.

Table B.6: Regression table – Probit model with endogenous selection. Dependent Variable: Financial Constraints

	I		II		III		IV		V	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
region 1	0.280*	0.131	0.280*	0.131	0.276*	0.131	0.231	0.122	0.274*	0.132
region 2	-0.276**	0.089	-0.275**	0.089	-0.272**	0.089	-0.250**	0.087	-0.272**	0.089
size	0.756	0.971	0.750	0.944	0.782	0.939	0.155	0.855	0.580	0.998
age	0.940	0.747	0.935	0.742	0.967	0.738	0.562	0.667	0.849	0.763
subdidiary	-0.294***	0.064	-0.294***	0.064	-0.295***	0.064	-0.287***	0.064	-0.292***	0.064
$age * size$	-2.562	1.568	-2.548	1.554	-2.635	1.545	-1.765	1.391	-2.357	1.603
exp inno	0.028	0.137	0.037	0.129	0.056	0.125	-0.089	0.097	-0.016	0.133
inno inc	0.212	0.162	0.213	0.162	0.211	0.162	0.173	0.161	0.206	0.163
inno rad	0.030	1.271	0.002	1.145	0.111	1.111	0.918	1.019	0.377	1.226
real result +	-0.142	0.077	-0.144	0.077	-0.145	0.075	-0.104	0.073	-0.129	0.080
real result -	0.041	0.101	0.047	0.096	0.059	0.093	0.036	0.086	0.012	0.100
exp result +	0.152	0.080	0.150	0.080	0.146	0.080	0.145*	0.072	0.170*	0.084
real result -	0.054	0.099	0.054	0.099	0.054	0.098	0.040	0.089	0.062	0.099
imp tech	0.025	0.099	0.025	0.099	0.024	0.099	0.024	0.099	0.027	0.099
imp ipr	0.105	0.106	0.105	0.106	0.104	0.106	0.094	0.106	0.103	0.106
imp market	0.001	0.070	0.000	0.070	0.000	0.070	0.011	0.070	0.003	0.070
$inno\ rad * age^{rev}$	-1.380	1.730	-1.350	1.464	-1.462	1.411	-2.624*	1.270	-1.923	1.607
$inno\ rad * size^{rev}$	0.984	1.456	0.996	1.452	0.926	1.454	0.792	1.364	0.984	1.442
athrho	-0.041	0.748	-0.134	0.607	0.575	-0.600	4.623	60.859	0.804	0.520
rho	-0.041	0.747	-0.134	0.596	-0.330	0.513	1.000	0.023	0.392	0.680
N stage 1	2,093		2,093		2,093		2,093		2,093	
N stage 2	1,061		1,061		1,061		1,061		1,061	
Wald chi2	48.160		53.300		47.460		82.680		61.520	
Prob > chi2	0.010		0.006		0.022		0.000		0.001	
log-likelyhood	-2,050		-2,044		-2,046		-2,046		-2,049	

*, **, *** indicate significance at 10, 5, 1 percent level

Paper C

Incremental by Design? On the Role of Incumbents in Technology Niches – An Evolutionary Network Analysis

Daniel S. Hain[†] and Roman Jurowetzki[†] [†] *IKE, Department of Business and Management, Aalborg University, DK*

The paper has been conditionally accepted for publication in the
Journal of Evolutionary Economics

The layout has been revised, and a preface not included in the original article has been added.

Abstract

In this paper, we study the influence of incumbent firms on the structural dynamics research networks in technological niches at the case of public funded research projects. The protected space of technological niches offered by such public research funding offer firms an environment to experiment in joint learning activities on emerging technologies shielded from the selection pressure on open markets, thereby facilitating socio-technological transitions. Generally, the engagement of large incumbent actors in the development of emerging technologies, particularly in joint research projects with entrepreneurial ventures, is positively perceived, since their resource endowment enables them to stem large projects and bring them all the way to the market. However, growing influence of incumbents might also alter niche dynamics, making technology outcomes more incremental and adapted to the current socio-technological regime. Potential influence on rate and direction of the technological development can to a large extend be explained by an actor's position in the network of the niche's research activities. We create such a directed network of project consortium leaders with their partners to analyze if network dynamics of joint research projects in technological niches favor incumbent actors in a way that they are able to occupy central and dominant positions over time. We deploy a stochastic actor-oriented model of network evolution at the case of Danish public funded "smart grid" research in the 2009-2012 period. We indeed discover path-dependent and cumulative effects favoring incumbents. Our findings suggest a development of the network towards an incumbent-dominated structure.

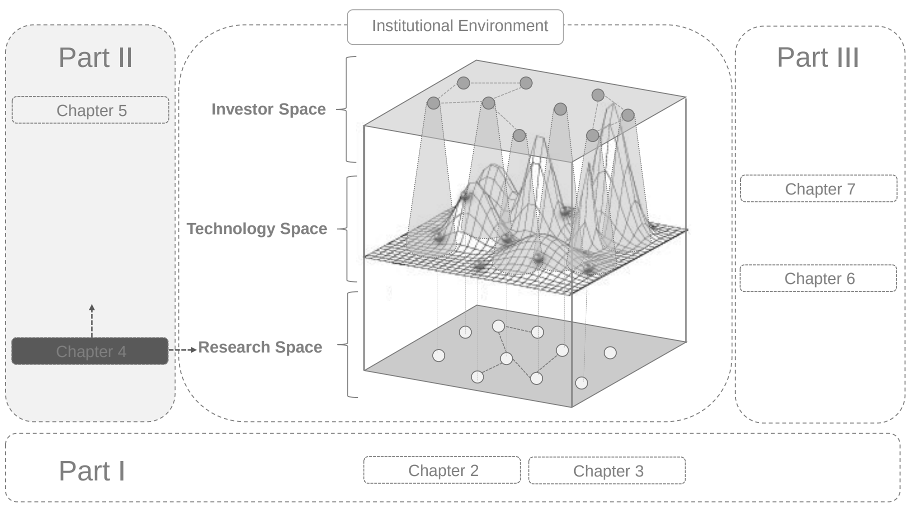
Preface

This thesis mostly focuses on the effect of networks within the finance sphere or between finance and research/industry, threatening network pattern and dynamics in the research sphere as exogenous. I argue that, for the sake of simplicity, one can – at least in the short run – assume analytic orthogonality between the dimensions of technological change. Yet, ample empirical evidence suggests that a firm's strategic positioning in interorganizational networks may affect its innovative performance (e.g. Baum et al., 2000; Powell et al., 1996), and the structure of the overall network affects the innovation output on the aggregated (Fleming et al., 2007) and firm level (Kudic, 2014; Schilling and Phelps, 2007) alike. Consequently, understanding network dynamics in research helps us to discuss the impact finance may play in facilitating the formation of favorable network structure.

In this chapter, my co-author Roman Jurowetzki and I therefore investigate the dynamics of heterogeneous firm strategies, resulting network patterns, and the rate and direction of technological change in public funded R&D projects in danish smart-grid research. Since such networks are to a large extent constructed by policy and the resulting grant allocation pattern, it provides an interesting setting to discuss how "policy-motivated investors" are able to influence network dynamics in research. We here focus on a theoretical as well as political tension, namely the role of large incumbent firms in such research projects and networks.In innovation system literature and many policy initiatives, engagement of large incumbent actors in the development of emerging technologies, and especially joint research projects together with young SME's, is generally positively perceived as they have the capabilities to fulfill necessary systemic functions in a better way than new start-up firms (Bergek et al., 2013a; Bulathsinhala and Knudsen, 2013). Yet, literature on socioeconomic transition and the multi-level perspective (Geels, 2002) provides a more critical perspective, arguing the involvement of incumbents might however alter niche dynamics making technology outcomes more incremental and adapted to the current unsustainable socio-technical regime. This is particularly evident if the emerging technology is a potential substitution to the existing solutions (Bower and Christensen, 1995b). The incumbents' ability to influence the trajectory of technological development can, to a large extent, be explained by their position in the niche network of early stage research. A stochastic actor based network analysis suitable to investigate the path dependent evolution of actor driven networks reveals that, in fact, large incumbent companies over time become increasingly dominant in the networks of actors that develop the Danish smart grid. Main forces behind this development we find on the supply side of public grant allocation, for instance the preferences of public authorities towards certain firms, technologies, project types. In addition, I identify demand side effects related strategic motives of incumbents to participate in technological niches.

By emphasizing governance and influence related aspects combined with firm characteristics and strategies, I provide an alternative – and perhaps more critical – perspective on research and innovation networks, and the role of the state in their coordination. Methodologically, I demonstrate the richness of novel techniques of evolutionary network analysis to answer such questions by modeling collaboration decisions on actor level, and relating them to macro outcomes of structural network evolution. This chapters aims to generally enhance our understanding of the hidden strategic choices of actors, their effect on the resulting network structure, and technological changes achieved rate and direction of technological change as an outcome. In the guiding framework of the Ph.D. thesis, it mainly focuses on the dynamics within the research space, but also links to outcomes in technology space and the influence of the institutional framework. The consideration of such strategic motives within research networks is of particular importance in sectors where incumbents generally enjoy large influence, and long life-cycles and high capital intensity of infrastructure investments offer potential incentives to enforce the current "status quo".

Fig. C.1: Positioning the paper in the theoretical framework



This paper was developed by merging ideas from one of my working papers on the evolution of danish energy research networks (Hain (imeo), presented at the DRUID winter academy 2013, Aalborg) and Roman's research on the influence of incumbents in energy research projects (Jurowetzki (2013b), presented at EMEAEE 2013, Nice). It was firstly presented at the the "1^{st} ENIC workshop" 2013 in Halle, afterwards at the "6^{th} AIE conference" 2014 in Oxford, the "15^{th}ISS conference" 2014 in Jena, and several other occasions at internal and external research workshop. It was submitted to the ISS book proceedings of the *Journal of Evolutionary Economics*, where it just got accepted for publication conditional of the consideration of the reviewers (which are not implemented in the version to be found in my Ph.D. yet).

1 Introduction

The multidisciplinary literature on system innovation, often empirically focused on sustainability transitions, outlines the significance of niches for the protection and development of path-breaking technologies in early stages (Geels, 2002, 2004; Hoogma et al., 2004; Kemp et al., 1998). Public funded research, development and demonstration (R&DD) protects represent such a protected space, offering firms an environment to experiment in joint learning activities on emerging technologies.

Even though the niche is not an explicit concept within the innovation systems literature, the Technological Innovation Systems (TIS) approach highlights the importance of creating protected spaces to foster market formation and diffusion (Bergek et al., 2008; Hekkert et al., 2007b).

Both streams of literature share a systemic understanding of innovation and acknowledge evolutionary phenomena such as path-dependency, lock-in, nonlinearity and multiple interdependency. However, there is arguably one significant difference between the frameworks: The TIS approach has been criticized for being “inward looking” (Markard and Truffer, 2008), in a way that it underplays the potential tension between path-breaking innovations and established technologies, or more broadly the selection environment.

The engagement of large incumbent actors in the development of emerging technologies, and especially joint research projects together with young SME’s, is generally positively perceived as they have the capabilities to fulfill necessary systemic functions in a better way than new start-up firms (Suurs and Hekkert, 2005). Apart from the direct effect of the engagement, it is likely to have a positive signaling effect. Thus, it might contribute positively to the status of the niche, improving financial credibility and triggering interest of other companies (Smith et al., 2005). Arguably, the involvement of incumbents might, however, alter niche dynamics, making technology outcomes more incremental and adapted to the current unsustainable socio-technical regime. This is particularly evident if the emerging technology is a potential substitution to the existing solutions (Bower and Christensen, 1995a; Tushman and Anderson, 1986). The incumbents’ ability to influence the trajectory of technological development can, to a large extent, be explained by their position in the niche network. A firm’s strategic positioning in interorganizational networks may affect its innovative performance (e.g. Baum et al., 2000; Powell et al., 1996), and the structure of the overall network affects the innovation output on the aggregated (Fleming et al., 2007) and firm level

(Schilling and Phelps, 2007; **?**) alike. If path-dependent and cumulative characteristics such as reputation, age, or size of actors are main drivers of change in these networks, evolutionary processes will enable them to obtain central and dominant positions and thus shape the niche's further development by their will.

Networks are by no means static constructs in time and space, but rather constantly rearrange in an evolutionary process (Doreian and Stokman, 2005; Powell et al., 2005) and call for more dynamic and evolutionary approaches in empirical innovation network research (e.g. Ahuja et al., 2007; Cantner and Graf, 2011). More recent studies provide sound reasoning and empirical evidence as to how cumulative and path dependent forces strongly influence the actor composition, structure and outcome of networks. If the current network structure impacts its possible future development, the network evolution becomes a path dependent and endogenous process (Kilduff and Tsai, 2003). Existing ties often tend to become more persistent over time (Burt, 2000), and preferential attachment makes the likelihood of creating new ties influenced by the actors stock (Barabási, 2005) – leading to a process of structural reinforcement (Gulati, 1999).

In the terminology of innovation and transition literature, that relates to the development of a niche into a "proto-regime" (Geels and Raven, 2006) with increasingly established institutions and emerging stabilization mechanisms. Actors in central positions of such networks are likely to have a high influence on the rate and direction of future research through their higher social influence and their role as "knowledge hubs". In public funded R&DD networks, consortium leaders of such projects based on public grants additionally have the opportunity to determine the content of research as well as the inclusion of further organizations. However, an actor's ability to successfully obtain research grants is also said to develop in a cumulative and path dependent manner (Viner et al., 2004). While these stabilization mechanisms are well-known features of social networks (e.g. Barabási and Albert, 1999), we know very little about how the characteristics and rationales of central actors affect the outcome of such networks. Incumbent actors, who over time carried out fixed investments in infrastructure, developed technological competences and secured market shares have a high incentive to protect and replicate the old regime's logic and reinforce existing technological trajectories rather than develop new ones (Geels, 2011). This reflects a more critical and nuanced consideration of network structures in research collaborations, which may not necessarily be fully cooperative and consensus oriented, as mostly envisioned in innovation system and networks oriented approaches. Following that argumentation and first empirical evidence (c.f. Jurowetzki, 2013a), actor driven network dynamics in technological niches can be assumed to lead to more incremental outcomes which reinforce old technological paths if (i.) the network evolution is driven by endogenous and cumulative effects, such as the actors size, age, reputation or network position; (ii.) incumbent actors embodying such characteristics are involved; and (iii.) there exist possible new niche trajectories which lead to an underutilization of their accumulated resources.

Empirically, this paper explores the evolution within the Danish electricity grid-infrastructure network of joint participation in public funded R&DD projects in the period 2009 until 2012. Companies and projects were identified by exploring the Danish research project database. The Danish case is of particular interest because of the explicit political aspiration to become a European technology hub for the development and testing of advanced energy grid technologies (KEMIN, 2013). A national smart grid strategy from May 2013 emphasizes the importance of interaction between research institutes, utilities and technology producers, and the development of various technologies. A number of research programs were established to support R&DD projects from basic research to large-scale demonstration and commercialization.

The purpose of the present paper is to study structural dynamics and path dependencies of research networks in technological niches at the case of public funded research projects. In particular, deploying a stochastic-actor-based model (Snijders et al., 2010a), we analyze if network dynamics of public funded R&DD in technological niches favor incumbent actors in a way that they are able to occupy central and dominant positions. Against the empirical and theoretical background, we conceptualize the research network as consisting of directed ties between the actors, assuming the project-leader to project-partner link as a hierarchically ordered relationship. By doing so, we are able to analyze up to now unobserved cumulative and self-reinforcing effects of network dynamics.

As a result, we indeed find such path-dependent and cumulative effects in the development of the research network that favor incumbent actors, in the long run leading to a a reinforcing process of structural stabilization with central and influential positions.

The remainder of this paper is composed as follows: The following section 2 aims at linking different streams of literature that advocate for the creation and protection of technological niches with network theory. This connection is made to understand strategies of different niche actors and possible macro outcomes of their behavior. Section ?? provides an overview of the technological and policy context of the smart grid development in Denmark. In section ?? we introduce the stochastic actor-based model deployed to identify the evolution in the niche-network, and describe the research networks data used for the analysis as well as our empirical strategy. Section 5 presents the results, and the final section 6 concludes.

2 Theoretical Background

2.1 Inertia at micro and meso levels

The achievement of the sustainability goals in highly dependent on the determination and ability to transform a number of large technical systems (LTS's) worldwide. LTS's, such as the energy grid, the transportation or the agri-food sector build complex, extremely interwoven technical, economic, institutional and administrative structures (Hughes, 1987). Such sectors heavily build and rely on existing tangible and institutional infrastructures (e.g. development and trial systems, supplier and distribution networks, energy transmission grids, and other complementary assets). This dependence leads to high entry barriers in aforementioned industries and explains why key players are likely to be large companies (e.g. electric utilities, car manufacturers, railway operators).

Incumbent firms with substantial shares of their resources bound in an established technological regime are said to struggle in maintaining a certain level of innovation activity - particularly when facing radical, discontinuous technological change (e.g. Bower and Christensen, 1995b; Wagner, 2010).[1] In case of *competence-enhancing* technological innovation, established firms have incentives to actively engage in and support the development of the technology updating the existing (Gilbert and Newbery, 1982) regime.*Competence-destroying* innovation in turn appears as more likely to be pioneered by newcomers (Anderson and Tushman, 1990; Tushman and Anderson, 1986).

Over time, incumbents might also develop adoptive capabilities, enabling them to absorb knowledge on more radical novelties and combine it with their stock of knowledge to develop superior products and processes (Bergek et al., 2013b). This can be done i.a. by engaging in joint R&D projects with

[1]One can broadly distinguish between *competence-enhancing* innovation building upon existing technological and organizational structures, and *competence-destroying* innovation turning them obsolete (Tushman and Anderson, 1986). This distinction to a certain extent reflects the notions of *incremental* and *readical* innovation.

entrant firms or the acquisition of their technology (e.g. Wagner, 2010). However, once internalized, the absorbed novelty is likely to be aligned with existing resources in a complementary way. Therefore, when engaging in joint R&D projects, we assume that established firms – given the power – will influence technological trajectories in a way that makes the outcomes more compatible with their established assets and therefore potentially less radical.

Once a LTS has gained momentum these strategies become part of the resistance mechanisms against change on the system level (e.g. Van der Vleuten and Raven, 2006; Walker, 2000). In the most extreme case, this leads to inertia and lock-in (Arthur, 1989), as one might observe in our current fossil fuel dependent energy system Unruh (2000, 2002).

2.2 Large technical systems transition and lock-in

As these systems gain momentum, they also develop effective resistance mechanisms against change (e.g. Van der Vleuten and Raven, 2006; Walker, 2000). The resulting set-up creates a power and capability imbalance between usually small enterprises that are pioneering the development of sustainable solutions and incumbent actors (Hockerts and Wustenhagen, 2010). As long as production and distribution processes within existing trajectories are economically favorable, incumbents will not see urgent reasons to make large investments and reorganize existing production structures. On the contrary, they are most likely to defend the system against change (Walker, 2000). In the most extreme case this leads to inertia and lock-in (Arthur, 1989), as one might observe in our current fossil fuel dependent energy system Unruh (2000, 2002).

2.3 System innovation thinking

Technological change embedded in large systemic context has been conceptualized and analyzed throughout the past three decades. The technological innovation system TIS sub-orientation (Bergek et al., 2008; Carlsson and Stankiewicz, 1991; Hekkert and Negro, 2009) within the innovation system (IS) literature is increasingly used for the analysis of emergent industries on the basis of radically innovative technologies and the institutional and organizational changes that accompany the technological development (Truffer et al., 2012). A number of system functions (Hekkert et al., 2007b) focusing on the support and nurturing of emerging technologies are seen as intermediate variables between the structure of the system and its performance, emerging out of the interplay between actors and institutions (Jacobsson and

Bergek, 2011). While it is acknowledged that incumbent players may employ strategies to prevent disruptive innovation (Hekkert et al., 2007b), their participation in the TIS is generally seen as fruitful – highlighting their resources, knowledge integration capabilities (e.g. Bulathsinhala and Knudsen, 2013) and the positive signalling.

In the recent decade, a second stream of literature situated closer to the science, technology and society (STS) tradition gained considerable attention. The multi-level perspective (MLP) at the center of the transition literature explains socio-technical transitions by the interplay of three systemic concepts. The landscape on the macro-, the socio-technical regime on the meso-, and niches on the micro-level respectively (Geels, 2002, 2005). The character and intensity of the interplay between the three levels define the paths, which a socio-technical transition might take. The key concept of the MLP is the regime, which represents a coherent, stable structure at the meso-level, combining established products, technologies, and institutions (routines, norms, practices). The regime is characterized by a high level of "structuration" (Coenen and Díaz López, 2010), well articulated rules, and hence path-dependency and mechanisms for self-stabilization. It corresponds in many respects to the selection environment in terms of evolutionary economic theory and generates entry barriers for innovative technologies.

2.4 Niches & protected spaces

Niches are conceptualized as spaces that shield path-breaking innovations in early stages of development from selection pressure on mainstream markets (Hoogma et al., 2004; Kemp et al., 2001; Schot, 1992). Due to alternative selection criteria, population and interaction dynamics, niches can develop own technological trajectories substantially differing from the established regime.

Selecting the appropriate level of protection and upholding a continuous assessment might be crucial, in order to prevent protection of poor innovations (Hommels et al., 2007) or on the other hand a too low level of protection (Smith and Raven, 2012). The latter can happen when actors belonging to the established unsustainable technological regime achieve dominance in spaces that are actually meant for the development of solutions that are potentially meant to replace parts of the current regime.

The direct funding of R&DD in selected technologies of interest represents an integral component of modern innovation policy. Shielded from the selection pressure of open markets, these research projects present an ideal platform for a broad, experimental and long term oriented search for new technologies. Nurtured with public investments, new entrants and incumbents alike are able to stem projects which would, due to their high technological uncertainty and long payoff periods, not be carried out otherwise. Given the proper institutional set-up, public R&DD financing offers a powerful tool to directly influence rate and direction of research activities (Pavitt, 1998) and to create technology niches.

2.5 A network perspective on technological niches

Cooperation and interaction between various actors involved in processes of technology development such as universities, firms, intermediate, and end users, are said to be of high importance for the smooth functioning of innovation systems (e.g. Hekkert et al., 2007a; Lundvall, 1992; Malerba, 2002). A major task for science and innovation policy is therefore to facilitate the development of favourable R&D network structures (Carlsson and Jacobsson, 1997), triggering interaction between heterogeneous actors and the generation of technological variety. Organizations form collaborative alliances in order to get access to their partners' technological assets and capabilities. Potentially fruitful interaction with other corporations come at the risk of opportunistic technology appropriation by the counterpart, making careful selection of partners crucial (Li et al., 2008).

One can broadly distinguish between two categories of information that actors can use in cooperation decisions. First, reputation, mostly stemming from past performance in similar settings (Shapiro, 1983). Second, information about an actor's position in relevant networks (Benjamin and Podolny, 1999; Burt, 1992; Granovetter, 1973). Both appear to be highly interdependent, since an actor's reputation can be influenced by the reputations of past and current exchange partners (Benjamin and Podolny, 1999; Podolny, 1993) and collective reputations can be transferred to the a groups individual actors (Schweizer and Wijnberg, 1999). In addition, in our case we assume that it is the leaders of the particular projects that higher influence on the composition of the collaborations. They are usually the ones applying for and holding the largest share of the corresponding grant. Consequently, they determine most of it's content, and selecting partners.

2.6 Summary

Overall, the above presented streams of literature draw a similar picture from their respective point of view: Innovation is particularly complex and costly in systemic set-ups. Path dependencies are especially pronounced in sectors with a high share of infrastructure. Frameworks that inform policy measures to spur change in these areas agree on the need to actively create technological and market niches in order to foster alternative technologies and in general solutions. Yet, the role of incumbent player within these niches needs more inquiry.

Innovation paths that are compatible with regime technologies are attractive for established firms. Resulting innovations can address some of the existing problems on the MLP-regime level without compromising existing socio-technical structures. Established firms are therefore likely to initiate or engage in niche activities, such as R&DD projects, which investigate such applications.

Facing radical or architectural technological change, they will not directly support the early development of path-breaking innovations, but rather aim at gaining control, acquiring, and integrating novel and existing technologies (Bergek et al., 2013b; Pavitt, 1986). Strong ties to the existent structures and technologies on the one hand and technological uncertainty, on the other lead to a relatively late but determined entry of incumbents into the development of these technologies. We assume that this may alter the particular innovative technology towards a less radical solution. In the case of sustainable technologies that would mean that generally more desirable superior solutions are possibly devaluated as they become compatible with the existing unsustainable system. From a policy perspective, and in the particular context of public research funding, that also raises the question related to *outcome additionality*.

3 Sociotechnical context of the smart grid development in Denmark

In order to understand and assess the structural dynamics of Danish energy R&DD projects, it is important to consider the technological and policy context of the smart grid development. This section will introduce the fundamental technological concepts, components, and challenges related to the ongoing paradigm shift in the Danish and many other energy systems. Furthermore, the second part of this section will provide a brief overview of the policy ambitions that inform and guide the setup of publicly funded research programs. While we fully acknowledge that funding programs and specified calls are likely to direct the technological trajectories of research projects, and to some extent predetermine their composition, certain types of evolution of the combined network might indicate politically unintended developments.

3.1 Paradigm shift in energy grids

The traditional architecture of the electricity grid assumes a unidirectional energy flow from centralized energy plants via the transmission and distribution grids to consumers, where energy production levels are constantly adjusted to match the over time fluctuating energy demand (Farhangi, 2010; Fox-Penner, 2010). Embracing the renewable energy paradigm, centralized energy production is gradually replaced by decentralized energy farming. The harmonization between production and consumption has to move from the traditional generation side into the transmission and consumption areas. ICT technologies will play a central role in supporting this process (Mattern et al., 2010).

In the Northeuropean set-up, two options are possible and currently discussed. Firstly, the construction of a European transmission super-grid to allow, for instance, energy exports from Denmark to Germany in wind-peak times. Secondly, the development of a national *smart grid*, that is able to transmit energy and information in both ways, thus allowing for harmonization by the means of flexible consumption. This requires the upgrade of the existing grid by adding a *layer of intelligence* - advanced measurement, communication and control technology - thus making the grid able to handle a higher share of decentralized renewable energy generation and the recently evolving consumption patterns (Elzinga, 2011). If flexible consumption can be activated by the introduction of smart functionality, costly investments in the reinforcement of the distribution system can be moved into the future or avoided (Forskningsnetværket, Smart Grid, 2013).

3.2 Danish smart grid research and aspirations

Denmark is already today counting the largest amount of R&DD projects within the smart energy area in Europe (Giordano et al., 2011, 2013). The extremely high ambition of the national energy agreement, passed by the government in 2012, targets a wind-power share of 50 percent by 2020, and the more recently announced Smart Grid Strategy sees the country as a European laboratory for innovative energy solutions (KEMIN, 2013). In their latest inventory report Giordano et al. (2013) outline, that compared with other European countries, Denmark manages to develop a large amount of smaller projects which spurs technological diversity (Borup et al., 2013). Figure C.2, adopted from (Jurowetzki, 2014), shows the various technology areas that can be summarized from an analysis of 99 research project descriptions.

The tagclouds, indicating particularly important keywords for the respective clusters, suggest that R&D projects can be broadly gathered in 10 groups. Projects in communities 8 and 9 are less technical, but rather focused on the interaction with the energy users and their ability to flexibilize consumption. Communities 5 and 7 examine different problems on a energy-sytem macro-level. Many of these projects develop models and simulations related to problems that stem from large scale renewable energy integration. The smaller communities, 0 and 1, summarize projects on data-transfer and advanced battery technology respectively. The communities 6 and 2 gather different projects related to electric mobility and its compatibility with the energy grid. Finally, the clusters 4 and 11 examine the role of the heating sector within the evolving grid infrastructure. Space and water heating is responsible for a great share of energy consumption, and due to its nature heating can be used as a source of flexible energy consumption and potentially also for energy storage. Research projects in this area mainly focus on the integration of mature heating technologies such as district heating and heat pumps into the emerging smart grid infrastructure.

While the obvious technological diversity can be interpreted as a sign of successful niche development and the gradual merge of the electricity and heating systems into one smart energy system (Copenhagen Cleantech Cluster, 2014), this context also offers entry and influence opportunities for different types of established actors. This study aims at exploring this issue, employing an evolutionary network study approach. At the core of this research is the question of whether public funded R&DD activities are able to provide necessary shielding in order to develop and introduce the needed amount of technological variety in the changing energy grid sector.

4 Modelling Network Evolution

4.1 Data

Network Data

As a source for public funded research projects, we utilize the database provided by *Energiforskning.dk*. Combining data from several energy technology research and development programs, this database represents the most comprehensive source for public funded energy research in Denmark, covering projects funded by the *Strategic Research Council, ForskEL, ForskNG, ForskVE, ELFORSK, Green Labs DK, Danish High Technology Foundation* and the *European Union*. For the current analysis records from the *smart grid and systems* category were exported containing information on projects from 2009 to 2012 on yearly basis – overall 75 projects with 277 participants, and 132 single firms. Among those actors we identify 27 incumbent firms and 21 research institutions with the rest being either established diversifier companies or new entrants[2]. A graphical presentation of the network under observation and its change over time is provided in Table C.3 in the appendix. On first glance, a formation of structural clusters around some incumbent actors can already be seen over time.

In order to utilize models of network dynamics, the dataset under observation has to fulfill certain properties in line with the underlying assumptions of this model class. First, the network has to show some variation between its periods. However, too rapid changes indicate that the assumption of gradual change – compared to the observation frequency – is violated. To ensure the validity of the gradual change assumption, we consult the Jaccard index to be found in table **??**, a common measure of similarity between two networks.[3] Snijders (2002) suggest this index to be higher than 0.3 and never drop beyond 0.2, which is given in our data. Overall, after a first preliminary inspection, the network data appears to have suitable properties in line with the assumptions of stochastic actor oriented models. Some further descriptive statistics on structural network measures and their development over time are provided in table **??** in the appendix.

Actor Data

Data on firm characteristics, such as their age, size, legal form *et cetra* was extracted from the Danish firm database Navne & Numre Erherv (NNE). For additional information about firms' technological capabilities and their range of activity where gathered by studying annual reports, press articles, corporate websites *et cetra*.

[2]A detailed description of the applied classification methodology is described below

[3]The Jaccard index as a measure of similarity between two network waves is computed by $\frac{N_{11}}{N_{11}+N_{01}+N_{10}}$, where N_{11} represents the number of ties stable over both waves, N_{01} the newly created and N_{10} newly terminated ties in wave 2 (see Batagelj and Bren, 1995).

4.2 Modeling network dynamics

Our attempt is to analyze the dynamics of interorganisational networks of joint participation in public funded research projects. In particular, we are interested in which firms over time move towards central positions in the network. The analysis of such dynamic networks represents an empirical challenge which calls for distinct statistical models and methods. The main problem stems from the very nature of social network formation processes. Many drivers of individual tie-formation decisions, such as transitivity, reciprocity, and popularity effects, by their very nature lead to endogeneity and dependencies of observations (Rivera et al., 2010), since multiple characteristics of the current network structure influence its future development. This usually violates the assumptions of most standard statistical model types at hand (Steglich et al., 2010).

The class of stochastic actor-oriented models (SAOM) originally developed by Snijders (1996) represents an attractive solution to address the inherent endogeneity problems of longitudinal network analysis, which scholars have lately started to deploy in the context of inter-organizational innovation networks (e.g. Balland, 2012; Balland et al., 2012; Buchmann et al., 2014; Giuliani, 2013; Ter Wal, 2013). At its core, a SAOM combines a random utility model, continuous time Markov process estimation procedures, and Monte Carlo simulation. Originally, SAOM was developed in a sociological context and designed to model group dynamics in interpersonal networks (e.g. Van De Bunt et al., 1999). However, actor-oriented modeling has also proven to be suitable to depict the interaction between macro outcomes and firms' micro choices (Macy and Willer, 2002; Whitbred et al., 2011) in inter-organizational alliance formation process. Here, structural change of the network is driven by individual firms' collaboration decision derived from a random utility model. Firms are assumed to observe the current network structure and characteristics of its population, and reorganize their ego-network in an utility-optimizing manner. Given the context of the study, we consider SAOM as the most suitable class of dynamic network models and deploy it for the empirical analysis to follow.

Snijders (1996) firstly proposed to address the problem of multiple endogeneity in the evolution of social network with transforming discrete datasets of panel waves into a continuous set of micro-changes (single reconfiguration decision) to be estimated by Markov-chain Monte Carlo simulation

(MCMC).[4] Unobserved changes between the panel waves are simulated as continuous actor choices at stochastically determined points of time. Formally, following a Poisson function of rate λ_i, the actors (in our case, individual firms) are allowed to create, maintain, or dissolve ties until the network is transformed to the new structure χ. The decision of actor i to change the state of one tie to another actor j leads to a new overall state of the network χ, where the probability P_i for an actor choosing this structure is given by:

$$P_i(\chi^0, \chi, \beta_k) = \frac{\exp(f_i(\chi^0, \chi', \beta_k))}{\sum\limits_{\chi' \in C(\chi^0)} \exp(f_i(\chi^0, \chi', \beta_k))} \tag{C.1}$$

It technically resembles a multinomial logistic regression, modeling the probability that an actor chooses a specific (categorical) new network configuration P_i as proportional to the exponential transformation of the resulting networks objective function $f_i(.)$, with respect to all other possible configurations. The parameters' coefficients are stepwise adjusted by Monte Carlo simulation techniques in order to obtain convergence between the estimated and observed model, and finally, held fixed to allow their comparison and post-estimation analyses. The objective function contains actor i's perceived costs and benefits of a particular network reconfiguration leading to a network state χ, χ, which are represented by the random utility model:

$$f_i(\chi^0, \chi', \beta_k) = \sum_k \beta_k s_i(\chi^0, \chi, \nu_i, \nu_j, c_{i,j}, \epsilon, r) \tag{C.2}$$

It depends on the current state of the network χ^0, the potential new one χ, the ego i's and alter j's individual covariates ν_i and ν_j, their dyadic covariates c_{ij}, exogenous environmental effects ϵ, and a random component r capturing omitted effects. The underlying assumption is that the actors observe the current structure of the network χ^0 and the relevant characteristics of its actor set and make their collaboration decisions in order to optimize their perceived current utility (Jackson and Rogers, 2007).

4.3 Empirical Strategy

Theoretical considerations

We model the tie creation process between ego i (project consortium leader) and alter j (project partner) as unidirectional from $i \Rightarrow j$. Thus, existing ties

[4] Besides all its merits, the usage of estimations based on continuous-time Markov processes also has its drawbacks. It by definition does not allow for path dependencies. Yet, it is still possible to include variables aggregated over time to the current state.

do not have to be reciprocal – a characteristic we find in many real-life networks such as friendships, mentorship, or producer-consumer relationships. Since we are interested in the ability to steer technological development of public funded research networks, we assume project consortium leader to have a significantly higher influence on the project's content than other participants. From this point of view, the directed network resembles the governance structure of there networks, and the actors outdegrees can be interpreted as a measure of influence. In our case, this appears as reasonable since the leaders of such projects are usually the ones applying for the corresponding grant, determining most of it's content, and selecting further partners. We chose a unilateral confirmation setup, where tie creating is only conditional to the ego's – but not the alter's – choice. By doing so, we assume potential partners to automatically join research projects when invited. This appears as a strong, but realistic assumption. Such a participation represents a safe source of income (and potentially knowledge), where the main upfront work, such as the grant application and determination of the content, is mostly carried out by the project leader. SAOM usually model tie creating as well as tie dissolution, where actors might choose to break up ongoing relationships which turn out to now offer negative utility. Since in our case the timeframe research projects is determined *ex-ante*, we only model the creation of new ties, where we exclude egos with already existing collaborations from the ego's choice set.

There undoubtedly exist some caveats when mapping networks based the common participation research consortia funded by public research grants. First, these networks only to some degree evolve naturally, since they are subject to a selection by the responsible public authorities. Selection criteria may be found, among others, in (i.) the reputation and credibility based on past performance and other forms of accumulated advantage of consortia members, (i.) the characteristics of the project such as the applied technology, (iii.) or the favoritism of certain consortia constellations. Second, since the actors are anticipating a selection according to these criteria, they have an incentive to consciously form consortia according to them. Thus, consortia formation are subject to selection biases *ex-ante* and *ex-post* to the project application. Consequently, the results have to be interpreted not as the outcomes of natural network evolution, but rather the channeled evolution in a socially constructed selection environment designed by public authorities, which might be subject to criteria (ii.). With the choice of the study's empirical context, we attempt to minimize systematic biases caused by criteria (ii.) and (iii.). First, Danish research funding in renewable energy technology is designed to generate the broad technological variety necessary for the sustainable transition of the energy system (Lund and Mathiesen, 2009), where favoritism of certain technology should explicitly be avoided. Second, by including several research funding programs of independent governmental and non-governmental agencies in Denmark and the EU, spanning different industries as well as preferred development stages of funded projects, we avoid systematic bias caused by preferences of particular programs or policy initiatives.

Yet, the development of the network in quest is driven by two forces. The supply side of public authorities making grant allocation decisions, as well as the (somewhat under-conceptualized) demand side capturing the firms decision to apply for grants, and their selection of partners. In our research setup, we will not be able to empirically disentangle them, which leaves us with intuition and anecdotal evidence.

Dependent Variable

We Model collaboration choices driving the evolution of the network are the outcome of the actors' mutual attempts to optimize their expected utility with respect to their own and their potential alters' covariates, and the current network structure. Thus, our model's dependent variable represents the probability P_i that the focal actor i chooses a reconfiguration of the own network that leads to a tie with a corresponding alter j.

Independent Variables

Actor covariates: This set of variables represents the effect of individual actor characteristics on their likelihood to establish new ties with other organizations.

In order to examine the `role` of actors in the combined network, we use a set of industry experts. We differentiate between three roles, where we are particularly interested in the role of energy incumbents and the strategic deviations of these actors as compared to other actors involved in smart grid research projects. `Role incumbent`: This category aims at grouping actors with an origin in the energy sector that have an vested interest in protecting the established infrastructure from significant change. The experts were asked to identify "firms with a strong background/track-record and stakes in the traditional energy sector". This includes utilities, producers of transmission and distribution infrastructure, and producers of measuring devises. Apart from the utilities that went through a Europe wide policy induced organizational restructuring process, companies were founded before 2000. `New Entrant`: This group summarizes companies which were mostly founded after 2000 and have their main activity in the energy sector. The firms provide a broad range of products and services. Many of the firms develop ICT related solutions for the envisioned communication structure of the smart grid. Another large share are technology consultancies that are often responsible for analysis and system integration. It, however, also includes mature firms from other fields diversifying in the energy sector. `Role Others:` This class contains private and public actors that have shown interest in the development of a new grid infrastructure by participating in a research project. Actors are rather heterogeneous and have not had a background in the energy grid sector. This set of actors represents the reference group.

The `size` of a firm is also supposed to influence it's capabilities of successfully obtaining research grants, as well as to occupy central and dominant position in the resulting research networks. However, `size` is difficult to compare between different forms of organizations such as private companies, public organizations and research institutions. Therefore we only use a rough categorical classification of small (up to 25 employees, `firm small`), medium sized (up to 100 employees, reference groups), and large organizations (more than 100 employees, `firm large`).

While maturing, firms are able to increase their competences in how to successfully formulate a research grant application, establish an intensify formal and informal relationships to industry partners and public authorities, and develop routines how to manage research partnerships. Since we expect these benefits to increase with decreasing marginal effects, and furthermore the distribution of firm age in our sample is highly skewed (start-ups as well as traditional firms established over a hundred years ago), we use the natural logarithm of the ego's `age` in years instead as control variable.

Some further descriptive statistics of these actor-oriented measures are provided in table C.6.

Local (ego) network effects: This set of variables captures structural characteristics of the actor's ego-network, which include dyadic and triadic tie-configurations with other actors. Literature suggests these effects to be among the most important driving forces of network dynamics. Given the context of our study, however, they mostly represent control variables and are not emphasized in the following analysis. Reason therefore is the local nature of these variables, referring to effects only in and on the close neighbourhood in the network space.

The most basic effect is defined by the `outdegree` of actor i, representing the basic tendency to form an arbitrary tie to possible alters j, regardless of their individual characteristics. Since most social network structures observed in reality are rather sparse (meaning their density is way below 0.5), this effect tends to be negative, meaning the costs of establishing a tie *per se* in absence of a particular beneficial characteristic outweigh the benefits if no further characteristics make this tie particularly attractive (Snijders et al., 2010a).

Another basic feature of most social networks is `reciprocity`, the tendency of an actor to respond to an $i \Rightarrow j$ with the establishment of an $j \Rightarrow i$ tie (c.f. Wasserman, 1979), or in our context to be invited to join a research project led by an organization formerly participated in a project led by the current organization.

`Transitivity` is a measure for the tendency towards transitive closure, sometimes also called the clustering coefficient. Formally, it determines the likelihood a connection between $i \Rightarrow j$ and $i \Rightarrow h$ is closed by a connection between $j \Rightarrow h$ and/or $h \Rightarrow j$, or in other words that "partners of partners become partners" (e.g. Davis, 1970). In our case we make use of the measure for transitive triads, which measures transitivity for actor i by the number of other actors h for which there is at least one intermediary j forming a transitive triplet of this kind.

Global network effects: Global network (or degree-related) effects express global hierarchies in a way that they reflect actors positions in the overall network. They capture the tendency of actors to form and receive ties according to their amount of out- and in-degrees, independent of their particular position in the network. They are of particular interest against the background of our study, since they are in contrast to commonly applied triadic measures suitable to analyze the tendency of certain actors to establish central and, thus, dominant positions in the network structure.

`Out-degree popularity` captures the reputation and social recognition effect of the network on the activities of actor i. A positive parameter indicates that actors sending a higher amount of ties are also considered as more attractive to receive them. This effect leads to a convergence of in- and outdegrees on actor level. In our case that indicates that actors leading many research projects also happen to often get invited to become research partners in other projects. These "knowledge integrators" (Bulathsinhala and Knudsen, 2013) are likely to accelerate the diffusion of knowledge and support other projects with their accumulated knowledge and other resources.

Of particular interest for this study is the `Out-degree activity`, which is the tendency of actors with high outdegrees to establish even more. A positive parameter indicates a self-reinforcing mechanism leading to an increasing dispersion of out-degrees in the network (Barabási and Albert, 1999). It can be interpreted as the in network-structuralic impersonation of what is called the “Matthew Effect” (c.f. Merton, 1968, 1988), cumulative advantage (Price, 2007) or preferential attachment (Barabási and Albert, 1999). Networks driven by this effect tend to stabilize towards a core-periphery structure around some very central, well connected, and influential actors.

To avoid collinearity with local network effects, both `Out-degree popularity` and `Out-degree activity` are used in their square root. We thereby also assume decreasing marginal effects of additional ties. Finally, we also include an interaction term between `Out-degree activity` and `role incumbent`, to test if the posited Matthew effect works particularly strong for incumbents.

Model Specification

To analyze the influence of actor characteristics and endogenous structural effects, we run a set of three models. All of them contain a set of standard structural dyadic and triadic ego-network control variables. Model I traditionally tests for ego (project leader) covariates, which are assumed to affect the capabilities of creating new outgoing ties. Model II instead tests for degree-related structural effects. In comparison to the set of dyadic and triadic structural effects, degree related effects are related to the overall number of in- and out-degrees of alter and ego, independent of their position in the others network. Thus, while the first set of controls refers to the local hierarchy of the actors ego network, degree related effects refer to a global hierarchy in the overall network. Finally, in model III we test for the joint effects of actor covariates and degree related effects simultaneously.

All parameters are estimated under full maximum likelihood according to the algorithm proposed by Snijders et al. (2010b), which has proven to be more efficient for small datasets. Technically, we make use of the SAOM application of SIENA (Ripley et al., 2013), a package for the statistical environment of R.

5 Results

Goodness-of-fit evaluation

As a first goodness-of-fit measure one can consider the t-convergence values of the parameters, indicating whether the simulated values deviate from the observed values. For a good model convergence, Snijders et al. (2010a) suggests to only include parameters with t-values of convergence between estimated and observed parameters below 0.1, what is given for all parameters in all corresponding models. The values in general show better convergence in later models, which confirms the effectiveness of our applied forward-selection strategy of model choice. Since the class of stochastic actor-oriented models is still under development, there exists no direct equivalent to the R^2 indicator of least squares regression models. Latest advances, however, offer a set of instruments to asses the model fit in stochastic settings. Score tests for each variable proposed by Schweinberger (2012), lead to overall satisfying results and gradually increased from model I to III. To account for changing dynamics over time, i.e. due to different policy focus and overall funding available, we carry out the test for time heterogeneity proposed by Lospinoso et al. (2011), which indeed shows a significant effect. As a result, an interaction term between year dummies and the actors outdegree is included in all models.

Also, we perform the Monte Carlo Mahalanobis Distance Test proposed by **?**. Here we test the null hypothesis that auxiliary statistics such as indegrees, outdegrees and geodesic distance of observe data is distributed the results of Monte Carlo simulations on the estimated coefficients of our SAOM model, using the network in period one as point of departure. The purpose is to evaluate how well our stochastic model simulates transformation from the initial to the final network in terms of different degree distributions. We thereby also provide first validation of the ability of our model to predict future developments of research networks based on our estimated coefficients. The results are illustrated in figure **??**. The results suggest that our model is very well suited to predict the indegree and geodesic degree distribution, where the simulation results are very close to the observed values. Same holds for most forms of triad constellations. The only weakness of the model up to now appears to be the inconsistent identification of low outdegrees. While the model performs very well for high outdegrees, the simulated statistics for nodes with zero up to two outdegrees deviates highly from the observed values. However, since we are primarily interested in the distribution of the high degrees (the dominant nodes in the network), we consider the accuracy of prediction on the low end only as second priority.

SAOM regression models

Table C.1 reports a set of SAOM on the probability of ego i to establish a new outgoing tie, depending on the egos characteristics, ego network, and global degree related effects. In our context that means that a project consortium leading firm i establishes a collaboration with some project partner firm j.

Table C.1: Stochastic Actor-Oriented Model: Probability of Tie Creation Ego→Alter

	Model I		Model II		Model III	
Variable	Coef.	Std. Er.	Coef.	Std. Er.	Coef.	Std. Er.
Structural ego-network effects						
outdegree	-4.314***	0.540	-5.913***	0.342	-6.264***	0.453
reciprocity	1.143	0.622	1.411**	0.582	1.034	0.594
transitivity	1.791***	0.345	0.319	0.228	0.229	0.191
Actor level effects						
size small	0.990	0.873			1.601**	0.681
size large	2.644***	0.832			1.629**	0.726
role incumbent	3.424***	0.611			2.759***	0.476
age (*ln*)	-0.793**	0.267			-0.448**	0.227
Degree related effects						
out-pop ($\sqrt{}$)			0.085**	0.029	0.077**	0.030
out-act ($\sqrt{}$)			0.372***	0.047	0.413***	0.073
out-act ($\sqrt{}$) $*$ role incumbent					1.430***	0.347

Note: *, **, *** indicate significance at 10, 5, 1 percent level, two-tailed

In the first model we jointly test for basic ego-network and ego-characteristic effects. `The outdegree` effect shows, as in most real-life sparse social networks, a negative coefficient. The positive and significant coefficient for `transitive ties` indicates local clustering over time, when partners of "partners become partners" on their on. Actors of `size large` establish significantly more outdegrees than their peers of `size small` or the `size medium` reference group. This might reflect the preference of grant allocation decision makers for more stable large firms leading research consortia, or just the higher resource endowments of large players enabling them to manage the coordination of multiple research projects simultaneously. The `age` of the firm, however, *ceteris paribus* manifests in decreasing outdegrees. Allocation preferences towards stable project leaders again should lead to favoring older firms not subject to the liability of newness and the associated high failure rate (Freeman et al., 1983). An explanation could instead be found on the demand side, when aging firms loose their innovative drive and stop engaging in early stage research. An interesting finding is the high positive and significant coefficient of `role incumbent`, providing first evidence that the smart grid research network indeed over time tends to be dominated by incumbent actors. Since we are not able to disentangle supply and demand effects of public research funding, this finding again offers different explanations. First, it can be interpreted of revealed preferences of public authorities for consortia led by incumbents, possibly reflecting incumbents strategic advantage of infrastructure ownership or their exercised influence on policy making. On the other hand, it is also possible that incumbents actively strive for consortia leadership positions enabling them to influence early stage research on the future energy grid infrastructure – possibly to preserve the "old regime".

In model II, we test for ego-network and global network degree-related effects. An interesting finding is that, after introducing global degree related network effects, the coefficient of `transitive ties` drops in magnitude as well as significance. This finding demonstrates the usefulness and additional insights of including degree related effects when analyzing directed networks. Since actors increasing high out- or indegrees, they naturally will also have more potential to form reciprocal ties in their choice set. However, in this case global centralization outweighs local clustering in the further evolution of the network, indicating the development towards a core-periphery rather than a small world like structure. Both `outdegree popularity` and `outdegree activity` show a high positive an significant coefficient, where `outdegree activity` dominates.[5] These findings indicate that the current selection environment in the technological niche of public funded smart grid R&DD indeed shows a tendency to develop towards a global hierarchy. This network-structural "Matthew Effect" over time leads to a development of the network towards a centralized network structure with a high dispersion of degrees. In such network structures, some actors continuously move in a reinforcing manner towards dominant positions. Such tendencies can be observed in many real-life networks. For instance, in a comparative analysis of different sectors of the Danish renewable energy research, Hain (imeo) finds universities to over time occupy central hub positions in the windpower as well as hydrogen research community. Thus, the question is which actors benefit from this effect.

Therefore, in model III we jointly test for the impact of ego-characteristic and global degree related network effects on an actor's establishment of further outdegrees. While ego-network effects remain roughly unchanged compared with the former model, the investigation of actor level effects reveal some interesting insights. Again, the effects of `size large` and `role incumbent` are significant and show positive coefficients, even though with decreased magnitude. However, among the degree related effects `outdegree`

[5]Note that all parameters in SAOM are standardized (divided by their mean), thus making a direct comparison of their magnitude difficult within a model, but easier between models.

`popularity` and `outdegree activity` both remain positive and significant, where the latter even increases in magnitude. Thus, `outdegree-activity` appears to be a major driving force in the evolution of public funded smart grid research networks, an effect that appears to be even stronger when controlling for firm characteristics.

Overall, the results of this final model suggests incumbents indeed to be in a favorable position to inherit dominant roles in the research network over time. While they are generally more likely to establish outgoing ties, preferential attachment and accumulated advantages reinforces this tendency over time, both in terms of in- and outdegrees. Finally , the interaction term `role incumbent * outdegree activity` also shows a high positive coefficient, significant at one percent level, providing further evidence for the advantageous effects incumbents enjoy in the development of their network position. Finally we introduce an interaction term between `outdegree-activity` and `role incumbent` to test if degree-related effects work particularly in favor of incumbent firms, which appears to be the case. Here we are able to provide evidence not only of the benefits incumbents *per se* in leading research consortia, but also that powerful mechanisms of network evolution work in their favor. If these effects are driven by the demand or supply side of public research funding can only be speculated. So may it be that incumbents due to factors like their political influence and ownership of the energy grid infrastructure are generally more successful in grant applications, but the ones who decide to massively exercise their influence on energy grid technology development will enjoy structural forces of network evolution supporting them to do so.

This process can easily be forecasted in a simple Monte Carlo simulation of network evolution using the parameters estimated in our SAOM for calibration. After 10 period, such a network already shows a very strong core-periphery structure, where the core is almost exclusively populated by incumbents.

Robustness test

Our results are primarily dependent on a correct classification of the actors' roles, which in our case is determined by the categorization of industry experts. To cross-validate these sensible results, we re-run all models with alternative classification strategies. First we apply a simple subjective classification strategy similar to the one used by Erlinghagen and Markard (2012), where we determine incumbents by certain combinations of NACE codes, size, and age of an actor. However, a classification exclusively based on these objective measures would often fail to identify actors. The list below presents the description of the three classes of actors. Second, we use a computational approach, where we collected approximately 550 Danish industrial publications related to energy system topics from the period 1995-2000 and used a fuzzy string matching approach in order to identify actors from the analyzed research projects within the texts. We assume that actors that appear in a "energy context" can be considered established in the industry. In all cases, the results point in the same direction but are less pronounced, which speaks in favor of using industry experts for the identification of nuanced roles such as energy incumbents.

6 Conclusion

In this paper, we studied the influence of incumbent firms on the structural dynamics of research networks in technological niches at the case of public funded research projects. Drawing from innovation system, sociotechnical transitions, and network evolution literature, we identify a set of structural – as well as firm-characteristic – effects that might enable incumbents over time to move towards dominant positions in the research network. These effects generally originate from the supply side of public grant allocation, for instance the preferences of public authorities towards certain firms, technologies, project types. In addition, we identify demand side effects related to strategic motives of incumbents to participate in technological niches, and draw implications for the rate and direction of technological change as an outcome of research network dominated by incumbents.

To do so, we conduct a stochastic actor-oriented network analysis, where we model the hierarchy and power structure in the network with directed ties between research project leader and partners. We assume the leader of such projects as mainly influencing the context of conducted research as well as the selection of further participants, thus strongly influencing the development of technological trajectories in such niche networks. In contrast to mostly pronounced function of "knowledge diffusion" in research and innovation networks, we focus on governance structures as a result of project leadership. By doing so, we are able to analyse up to now unobserved cumulative and self-reinforcing effects of network dynamics and relate them to firm strategies and vested interests.

Our results indicate path-dependent and cumulative effects of firm characteristics such as size, and degree-related "Mathew effects" in the development of the research network, which over time lead to a centralization of the network structure. While we find incumbents *per se* to enjoy benefits in establishing new outgoing ties, we find path-dependent effects to work particularly in their favor. Overall, the observed dynamics suggest a development of the network towards a structure where incumbents occupy the most central positions.

By emphasizing governance and influence related aspects combined with firm characteristics and strategies, we provide an alternative - and perhaps more critical - perspective on research and innovation networks, and the role of the state in their coordination. Methodologically, we demonstrate the richness of stochastic actor-oriented models to answer such questions by modeling collaboration decisions on actor level, and relating them to macro outcomes of structural network evolution. We further contribute to a more nuanced discussion on the role and behavior of incumbents in sociotechnical transitions by identifying which firm-characteristics and structural forces of network evolution facilitate them to - for the better or the worse - increase their influence in the formulation of early stage research agendas. Our findings also provide implications for policy. Whether these increasingly incumbent-dominated networks are favorable or not is a rather normative discussion, which would go beyond the scope of this research.

However, the here unveiled interplay between firm characteristics, strategy and network dynamics have to be considered carefully, since they are to some extent policy orchestrated and not fully subject to natural evolution. The supply side selection environment is subject to *ex-ante* biases of grant allocation preferences of public authorities, as well as *ex-post* biases of firms observing these preferences and probably optimizing their project constellation patterns. Further, demand side effects related to firm strategies and vested interests affect the extent to which they participate in public funded research projects or choose other forms of collaboration, and which positions they prefer in such projects. While we derive some suggestions from theoretical reasoning and existing (mixed) evidence, we are not able to analytically disentangle supply and demand side effects. Even though this is supported by prior results on the same data (c.f. Jurowetzki, 2013a), we yet do not provide a direct analytic link between the identified structural change of research networks and outcome characteristics in terms of more radical or incremental innovation.

Consequently, we consider future research separating supply and demand side effects of public funded research network formation as a promising avenue for further research. Here, the combination of rich supply side data, such as evaluations of project grant applications together with firm-level data on motives and strategies appears to be particularly promising to disentangle supply and demand side effects in public funding of R&D and the resulting network dynamics. While the empirical link between the network structure and innovation outcomes can be – and has been – established using network data to explain innovation output measures such as patents, the link between micro-level actor behavior and network dynamics with macro-level outcomes faces some empirical challenges. One obvious challange is the endogeneity caused by interdependence of actor behavior and network position. Co-evolutionary models of networks and actor behavior as proposed by Snijders et al. (2007) and applied by Checkley et al. (2014); Steglich et al. (2010); Veenstra and Steglich (2012) could be an attractive solution. Furthermore, additional empirical cross-country and cross-industry evidence is needed to clarify the role of incumbents in research networks and sustainable transitions in general. We hope our work stimulates further work on this issue, which we consider as a promising avenue for future research.

References

Ahuja, G., Soda, G., and Zaheer, A. (2007). Call for papers: The genesis and dynamics of networks. *Organization Science*, 18(6):1024.

Anderson, P. and Tushman, M. L. (1990). Technological discontinuities and dominant designs: A cyclical model of technological change. *Administrative science quarterly*, pages 604–633.

Arthur, W. B. (1989). Competing technologies, increasing returns, and lock-in by historical events. *The economic journal*, 99(394):116–131.

Balland, P. (2012). Proximity and the evolution of collaboration networks: evidence from research and development projects within the global navigation satellite system (GNSS) industry. *Regional Studies*, 46(6):741–756.

Balland, P.-A., De Vaan, M., and Boschma, R. (2012). The dynamics of interfirm networks along the industry life cycle: The case of the global video game industry, 1987–2007. *Journal of Economic Geography*.

Barabási, A. and Albert, R. (1999). Emergence of scaling in random networks. *science*, 286(5439):509–512.

Barabási, A.-L. (2005). Emergence of scaling in complex networks. pages 69–84. Wiley-VCH Verlag GmbH & Co. KGaA, Weinheim, FRG.

Batagelj, V. and Bren, M. (1995). Comparing resemblance measures. *Journal of classification*, 12(1):73–90.

Baum, J., Calabrese, T., and Silverman, B. S. (2000). Don't go it alone: Alliance network composition and startups' performance in canadian biotechnology. *Strategic Management Journal*, 21(3):267–294.

Benjamin, B. and Podolny, J. (1999). Status, quality, and social order in the california wine industry. *Administrative Science Quarterly*, 44(3):563–589.

Bergek, A., Berggren, C., Magnusson, T., and Hobday, M. (2013a). Technological discontinuities and the challenge for incumbent firms: Destruction, disruption or creative accumulation? *Research Policy*.

Bergek, A., Berggren, C., Magnusson, T., and Hobday, M. (2013b). Technological discontinuities and the challenge for incumbent firms: Destruction, disruption or creative accumulation? *Research Policy*.

Bergek, A., Jacobsson, S., Carlsson, B., Lindmark, S., and Rickne, A. (2008). Analyzing the functional dynamics of technological innovation systems: A scheme of analysis. *Research Policy*, 37(3):407–429.

Borup, M., Klitkou, A., Andersen, M. M., Hain, D. S., Christensen, J. L., and Rennings, K. (2013). Indicators of energy innovation systems and their dynamics. a review of current practice and research in the field: Radar report. Eis radar report, EIS - Strategic research alliance for Energy Innovation Systems and their dynamics.

Bower, J. L. and Christensen, C. (1995a). Disruptive Technologies. Harvard Business Review.

Bower, J. L. and Christensen, C. M. (1995b). *Disruptive technologies: catching the wave*. Harvard Business Review Video.

Buchmann, T., Hain, D. S., Kudic, M., and Müller, M. (2014). Exploring the evolution of innovation networks in science-driven and scale-intensive industries: New evidence from a stochastic actor-based approach. IWH Discussion Paper 1/2014, 42.

Bulathsinhala, N. A. and Knudsen, M. P. (2013). The role of organizational knowledge integrators in large r&d projects. Conference proceeding, 35th DRUID Celebration Conference, ESADE Business School, Barcelona, Spain.

Burt, R. S. (1992). Structural holes: The social structure of competition. In Nohria, N. and Eccles, R., editors, *Networks and Organizations*, pages 57–91.

Burt, R. S. (2000). Decay functions. *Social networks*.

Cantner, U. and Graf, H. (2011). Innovation networks: formation, performance and dynamics. In Antonelli, C., editor, *Handbook on the economic complexity of technological change*, pages 366–394. Edward Elgar Publishing.

Carlsson, B. and Jacobsson, S. (1997). Diversity creation and technological systems: a technology policy perspective. *Systems of innovation: Technologies, institutions and organizations, London, Pinter Publishers*.

Carlsson, B. and Stankiewicz, R. (1991). In search of useful public policies: key lessons and issues for policy makers. *Journal of evolutionary economics*, 1(2):93–118.

Checkley, M., Steglich, C., Angwin, D., and Endersby, R. (2014). Firm performance and the evolution of cooperative interfirm networks: Uk venture capital syndication. *Strategic Change*, 23(1-2):107–118.

Coenen, L. and Díaz López, F. J. (2010). Comparing systems approaches to innovation and technological change for sustainable and competitive economies: an explorative study into conceptual commonalities, differences and complementarities. *Journal of Cleaner Production*, 18(12):1149–1160.

Copenhagen Cleantech Cluster (2014). The Smart Energy System. Technical report.

Davis, J. (1970). Clustering and hierarchy in interpersonal relations: Testing two graph theoretical models on 742 sociomatrices. *American Sociological Review*, pages 843–851.

Doreian, P. and Stokman, F. N. (2005). The dynamics and evolution of social networks. In P. Doreian, . F. N. S., editor, *Evolution of Social Networks*, volume 2nd edition, pages 1–17, New York. Gordon & Breach.

Elzinga, D. (2011). Smart Grids Roadmap. Technical report.

Erlinghagen, S. and Markard, J. (2012). Smart grids and the transformation of the electricity sector: ICT firms as potential catalysts for sectoral change. *Energy Policy*, 51(C):895–906.

Farhangi, H. (2010). The path of the smart grid. *Power and Energy Magazine, IEEE*, 8(1):18–28.

Fleming, L., King, C., and Juda, A. (2007). Small worlds and regional innovation. *Organization Science*, 18(6):938–954.

Forskningsnetværket, Smart Grid (2013). Roadmap for forskning, udvikling og demonstration inden for Smart Grid frem mod 2020. Technical report.

Fox-Penner, P. (2010). *Smart Power*. Climate Change, the Smart Grid, and the Future of Electric Utilities. Island Press.

Freeman, J., Carroll, G., and Hannan, M. (1983). The liability of newness: Age dependence in organizational death rates. *American Sociological Review*, pages 692–710.

Geels, F. (2002). Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and a case-study. *Research policy*, 31(8):1257–1274.

Geels, F. W. (2004). From sectoral systems of innovation to socio-technical systems. *Research Policy*, 33(6-7):897–920.

Geels, F. W. (2005). Technological Transitions and System Innovations: A Co-evolutionary and Socio-Technical Analysis.

Geels, F. W. (2011). The multi-level perspective on sustainability transitions: Responses to seven criticisms. *Environmental Innovation and Societal Transitions*, 1(1):24–40.

Geels, F. W. and Raven, R. (2006). Non-linearity and expectations in niche-development trajectories:. *Technology Analysis & Strategic Management*, (18):375–392.

Gilbert, R. J. and Newbery, D. (1982). Preemptive patenting and the persistence of monopoly. *The American Economic Review*.

Giordano, V., Gangale, F., Fulli, G., Jiménez, M. S., Onyeji, I., Colta, A., Papaioannou, I., Mengolini, A., Alecu, C., and Ojala, T. (2011). Smart Grid projects in Europe: lessons learned and current developments. *European Commission, Joint Research Centre, Institute for Energy, Luxembourg*.

Giordano, V., Gangale, F., Fulli, G., Jiménez, M. S., Onyeji, I., Colta, A., Papaioannou, I., Mengolini, A., Alecu, C., and Ojala, T. (2013). Smart Grid projects in Europe: lessons learned and current developments. *European Commission, Joint Research Centre, Institute for Energy, Luxembourg*.

Giuliani, E. (2013). Network dynamics in regional clusters: Evidence from Chile. *Research Policy*, 42(8):1406–1419.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, 78(6):1360–1380.

Gulati, R. (1999). Network location and learning: The influence of network resources and firm capabilities on alliance formation. *Strategic management journal*, 20(5):397–420.

Hain, D. S. (Mimeo). The evolution of networks in public funded renewable energy r&d in the technology llife-cycle. Aalborg University.

Hekkert, M., Suurs, R., Negro, S., Kuhlmann, S., and Smits, R. (2007a). Functions of innovation systems: A new approach for analysing technological change. *Technological Forecasting and Social Change*, 74(4):413–432.

Hekkert, M. P. and Negro, S. O. (2009). Technological Forecasting & Social Change. *Technological Forecasting & Social Change*, 76(4):584–594.

Hekkert, M. P., Suurs, R. A. A., Negro, S. O., Kuhlmann, S., and Smits, R. E. H. M. (2007b). Functions of innovation systems: A new approach for analysing technological change. *Technological Forecasting & Social Change*, 74(4):413–432.

Hockerts, K. and Wustenhagen, R. (2010). Greening goliaths versus emerging davids–theorizing about the role of incumbents and new entrants in sustainable entrepreneurship. *Journal of Business Venturing*, 25(5):481–492.

Hommels, A., Peters, P., and Bijker, W. E. (2007). Techno therapy or nurtured niches? Technology studies and the evaluation of radical innovations. *Research Policy*, 36(7):1088–1099.

Hoogma, R., Kemp, R., Schot, J., and Truffer, B. (2004). Experimenting for sustainable transport: The approach of strategic niche management. *Technology Analysis & Strategic Management*, 16(4):561–566.

Hughes, T. P. (1987). The evolution of large technological systems. *The social construction of technological systems: New directions in the sociology and history of technology*, pages 51–82.

Jackson, M. O. and Rogers, B. W. (2007). Meeting strangers and friends of friends: How random are social networks? *The American economic review*, pages 890–915.

Jacobsson, S. and Bergek, A. (2011). . *Environmental Innovation and Societal Transitions*, 1(1):41–57.

Jurowetzki, R. (2013a). Nichehunting? - Exploring the influence of incumbents on niche dynamics in transitions to sustainability. In *8th European Meeting on Applied Evolutionary Economics (EMAEE)*, pages 1–32.

Jurowetzki, R. (2013b). Nichehunting?-exploring the influence of incumbents on niche dynamics in transitions to sustainability. In *8th European Meeting on Applied Evolutionary Economics (EMAEE)*, pages 1–32.

Jurowetzki, R. (2014). Exploring Technology Evolution in Danish Smart Grid Development - An NLP approach. In *DRUID Academy Conderence*, pages 1–25.

KEMIN (2013). Smart Grid Strategy. Technical report.

Kemp, R., Rip, A., and Schot, J. (2001). Constructing transition paths through the management of niches. In Garud, R. and Karnøe, P., editors, *Path Dependence and Creation*, pages 269–299. Lawrence Erlbaum, Mahwah, NJ.

Kemp, R., Schot, J., and Hoogma, R. (1998). Regime shifts to sustainability through processes of niche formation: The approach of strategic niche management. *Technology Analysis & Strategic Management*, 10(2):175–198.

Kilduff, M. and Tsai, W. (2003). *Social Networks and Organizations*. SAGE Publications Limited.

Kudic, M. (2014). *Innovation Networks in the German Laser Industry: Evolutionary Change, Strategic Positioning, and Firm Innovativeness*. Springer.

Li, D., Eden, L., Hitt, M. A., and Ireland, R. D. (2008). Friends, acquaintances, or strangers? Partner selection in R&D alliances. *Academy of management journal*, 51(2):315–334.

Lospinoso, J. A., Schweinberger, M., Snijders, T. A., and Ripley, R. M. (2011). Assessing and accounting for time heterogeneity in stochastic actor oriented models. *Advances in data analysis and classification*, 5(2):147–176.

Lund, H. and Mathiesen, B. (2009). Energy system analysis of 100% renewable energy systems – the case of denmark in years 2030 and 2050. *Energy*, 34(5):524–531.

Lundvall, B.-Å. (1992). *National Systems of Innovation: Toward a theory of innovation and interactive learning*. London: Pinter Publishers.

Macy, M. W. and Willer, R. (2002). From factors to actors: Computational sociology and agent-based modeling. *Annual review of sociology*, pages 143–166.

Malerba, F. (2002). Sectoral systems of innovation and production. *Research policy*, 31(2):247–264.

Markard, J. and Truffer, B. (2008). Technological innovation systems and the multi-level perspective: Towards an integrated framework. *Research Policy*, 37(4):596–615.

Mattern, F., Staake, T., and Weiss, M. (2010). ICT for green. In *the 1st International Conference*, pages 1–10, New York, New York, USA. ACM Press.

Merton, R. (1968). The matthew effect in science. *Science*, 159(3810):56–63.

Merton, R. (1988). The matthew effect in science, ii: Cumulative advantage and the symbolism of intellectual property. *isis*, 79(4):606–623.

Pavitt, K. (1986). 'Chips' and 'Trajectories': How does the semiconductor influence the sources and directions of technical change? *Technology and the human prospect*, pages 31–55.

Pavitt, K. (1998). The inevitable limits of eu r&d funding. *Research Policy*, 27(6):559–568.

Podolny, J. (1993). A status-based model of market competition. *American journal of sociology*, pages 829–872.

Powell, W., Koput, K., and Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative science quarterly*, pages 116–145.

Powell, W. W., White, D. R., Koput, K. W., and Owen-Smith, J. (2005). Network dynamics and field evolution: The growth of interorganizational collaboration in the life sciences1. *American journal of sociology*, 110(4):1132–1205.

Price, D. (2007). A general theory of bibliometric and other cumulative advantage processes. *Journal of the American Society for Information Science*, 27(5):292–306.

Ripley, R. M., Snijders, T. A., and Preciado, P. (2013). Manual for siena version 4.0. Oxford: University of Oxford, Department of Statistics; Nuffield College.

Rivera, M. T., Soderstrom, S. B., and Uzzi, B. (2010). Dynamics of dyads in social networks: Assortative, relational, and proximity mechanisms. *Annual Review of Sociology*, 36:91–115.

Schilling, M. and Phelps, C. (2007). Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Science*, 53(7):1113–1126.

Schot, J. (1992). The policy relevance of the quasi-evolutionary model: the case of stimulating clean technologies. In Coombs, R., Saviotti, P., and Walsh, V., editors, *Technological change and company strategies: economic and sociological perspectives*. Academic Press, London.

Schweinberger, M. (2012). Statistical modelling of network panel data: Goodness of fit. *British Journal of Mathematical and Statistical Psychology*, 65(2):263–281.

Schweizer, T. and Wijnberg, N. (1999). Transferring reputation to the corporation in different cultures: Individuals, collectives, systems and the strategic management of corporate reputation. *Corporate Reputation Review*, 2(3):249–266.

Shapiro, C. (1983). Premiums for high quality products as returns to reputations. *The quarterly journal of economics*, 98(4):659–679.

Smith, A. and Raven, R. (2012). What is protective space? reconsidering niches in transitions to sustainability. *Research Policy*, 41(6):1025–1036.

Smith, A., Stirling, A., and Berkhout, F. (2005). The governance of sustainable socio-technical transitions. *Research Policy*, 34(10):1491–1510.

Snijders, T. (2002). The statistical evaluation of social network dynamics. *Sociological methodology*, 31(1):361–395.

Snijders, T., Steglich, C., and Schweinberger, M. (2007). Modeling the co-evolution of networks and behavior. *Longitudinal models in the behavioral and related sciences*, pages 41–71.

Snijders, T., Van de Bunt, G., and Steglich, C. (2010a). Introduction to stochastic actor-based models for network dynamics. *Social Networks*, 32(1):44–60.

Snijders, T. A. (1996). Stochastic actor-oriented models for network change. *Journal of mathematical sociology*, 21(1-2):149–172.

Snijders, T. A., Koskinen, J., and Schweinberger, M. (2010b). Maximum likelihood estimation for social network dynamics. *The Annals of Applied Statistics*, 4(2):567–588.

Steglich, C., Snijders, T. A., and Pearson, M. (2010). Dynamic networks and behavior: Separating selection from influence. *Sociological Methodology*, 40(1):329–393.

Suurs, R. and Hekkert, M. P. (2005). Naar een methode voor het evalueren van transitietrajecten. *Functies van innovatiesystemen toegepast op ′ ...*.

Ter Wal, A. L. (2013). The dynamics of the inventor network in german biotechnology: geographical proximity versus triadic closure. *Journal of Economic Geography*, 13(6).

Truffer, B., Markard, J., Binz, C., and Jacobsson, S. (2012). A literature review on Energy Innovation Systems. Technical report.

Tushman, M. L. and Anderson, P. (1986). Technological discontinuities and organizational environments. *Administrative science quarterly*, pages 439–465.

Unruh, G. (2000). Understanding carbon lock-in. *Energy policy*, 28(12):817–830.

Unruh, G. (2002). Escaping carbon lock-in. *Energy Policy*, 30(4):317–325.

Van De Bunt, G. G., Van Duijn, M. A., and Snijders, T. A. (1999). Friendship networks through time: An actor-oriented dynamic statistical network model. *Computational & Mathematical Organization Theory*, 5(2):167–192.

Van der Vleuten, E. and Raven, R. (2006). Lock-in and change: Distributed generation in Denmark in a long-term perspective. *Energy Policy*, 34(18):3739–3748.

Veenstra, R. and Steglich, C. (2012). Actor-based model for network and behavior dynamics: a tool to examine selection and influence processes. *Handbook of developmental research methods*, pages 598–618.

Viner, N., Powell, P., and Green, R. (2004). Institutionalized biases in the award of research grants: a preliminary analysis revisiting the principle of accumulative advantage. *Research Policy*, 33(3):443–454.

Wagner, M. (2010). Acquisitions as a means of innovation sourcing by incumbents and growth of technology-oriented ventures. *International Journal of Technology Management*, 52(1):118–134.

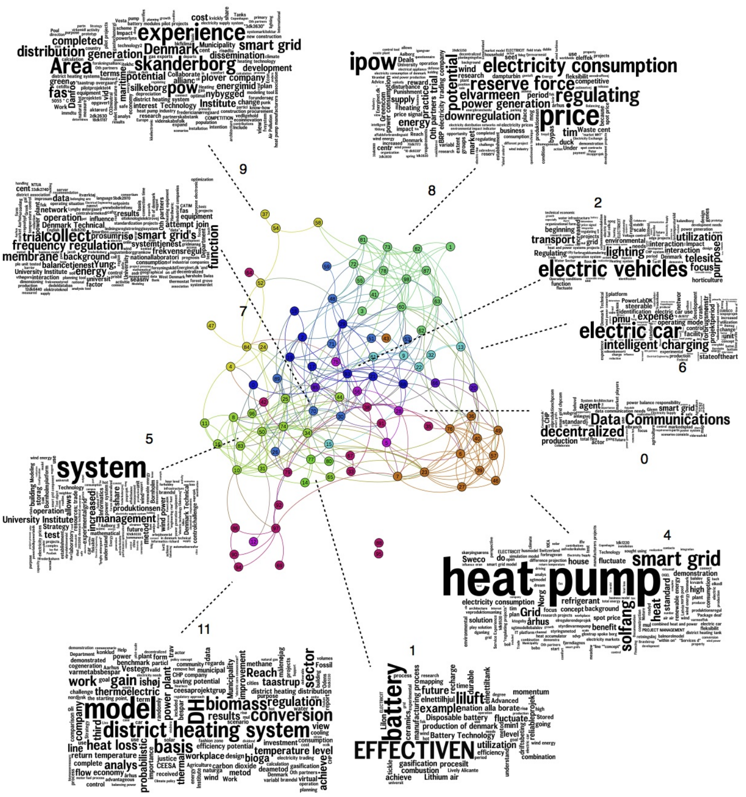
Walker, W. (2000). Entrapment in large technology systems: institutional commitment and power relations. *Research Policy*, 29(7):833–846.

Wasserman, S. (1979). A stochastic model for directed graphs with transition rates determined by reciprocity. In In: Schuessler, K., editor, *Sociological Methodology*, pages 392–412. Jossey-Bass, San Francisco.

Whitbred, R., Whitbred, F., Fonti, C., Steglich, N., and Contractor (2011). From microactions to macrostructure and back: A structurational approach to the evolution of organizational networks. 37:404–433.

Appendix

Fig. C.2: Research project graph and cluster level TFIDF-Keywords.



Note: Projects range from 1996 until 2013, what exceeds the later used data by approximately a third. The underlying analysis combines natural language analysis, vector space modelling and community detection within networks. A detailed methodology description and analysis can be found in Jurowetzki (2014)

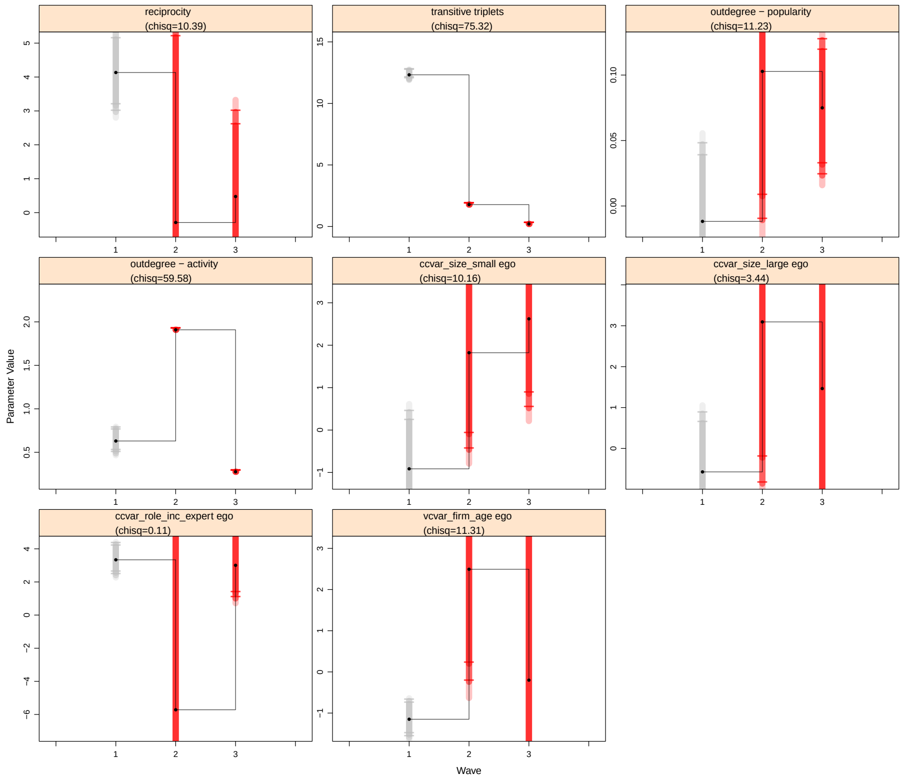


Fig. C.3: Test for time-heterogeneity following Lospinoso et al. (2011)

Table C.2: Illustration of Ego-Network and Degree-Related Effects

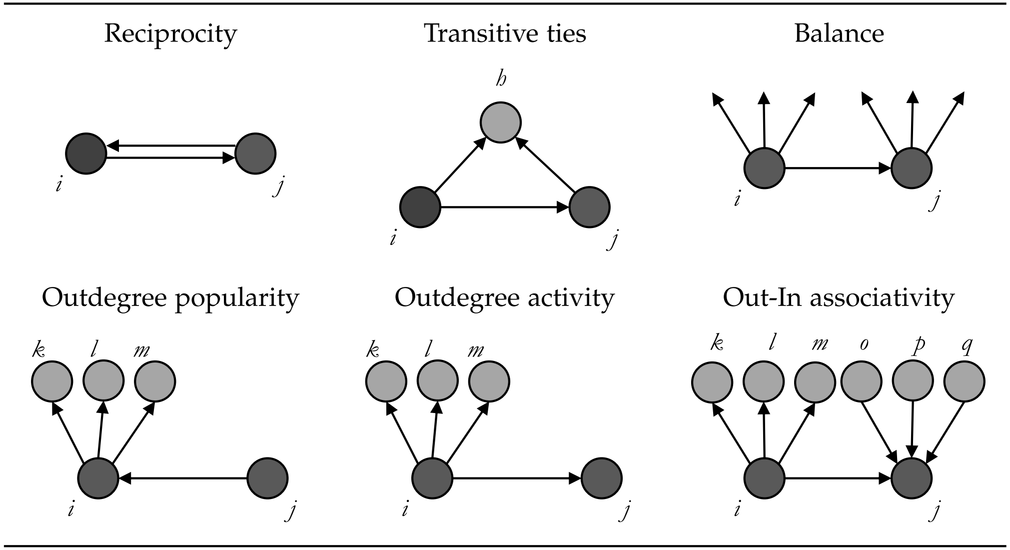
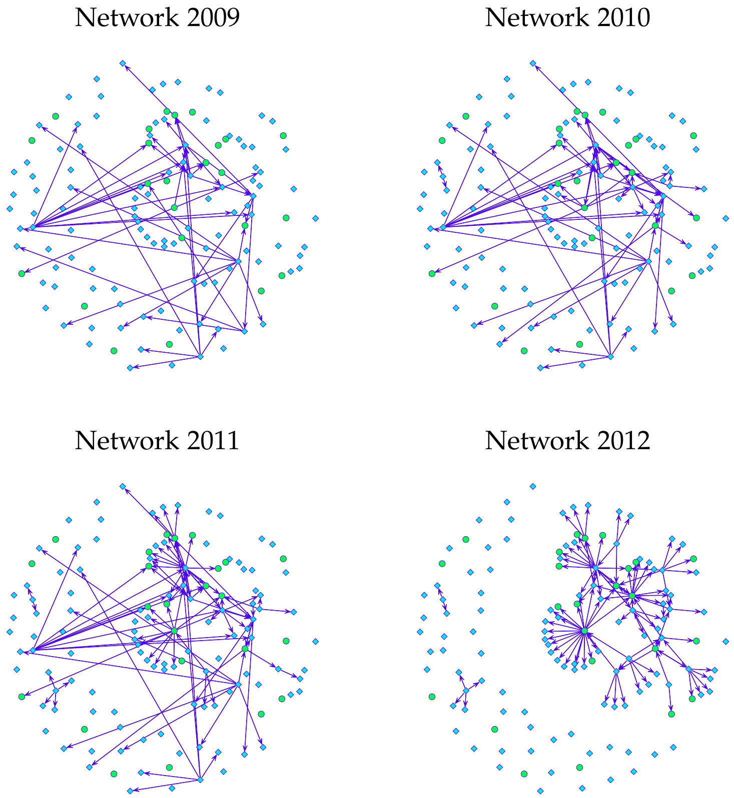


Table C.3: Network Development in Public Funded R&D in Smart-Grid Research



Note: Research network on basis of joint public funded research projects. Ties are directed from project-leader ⇒ project partner. Circles represent incumbents, squares all remaining types of organisations. The graphical presentation was done with the R package *Igraph*.

Table C.4: Network turnover frequency

Periods	$0 \Rightarrow 1$	$1 \Rightarrow 0$	$1 \Rightarrow 1$	Jaccard
$1 \Rightarrow 2$	22	3	42	0.627
$2 \Rightarrow 3$	30	2	62	0.660
$3 \Rightarrow 4$	53	39	53	0.366

Table C.5: Network density indicators

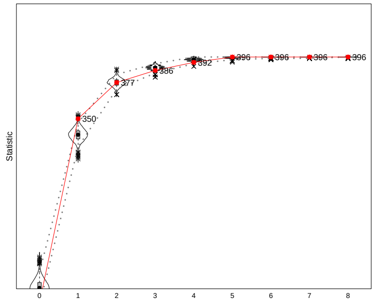
Periods	1	2	3	4
density	0.003	0.004	0.005	0.006
average degree	0.341	0.485	0.697	0.803
Network rate	0.383	0.490	1.406	-
number of ties	45	64	92	106
Mutual ties	0	2	4	3
Asymmetric ties	45	60	84	100

Table C.6: Descriptive Statistics

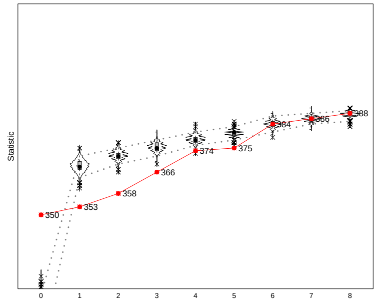
Variable	Min.	Max.	Mean	Std. Dev.
size small	0	1	0.356	0.481
size large	0	1	0.432	0.497
Role: Incumbent	0	1	0.182	0.387
Role: Newcommer	0	1	0.106	0.309
Firm age	1	110	22.437	22.130

Table C.7: Goodness-of-Fit: Monte Carlo Mahalanobis Distance Test

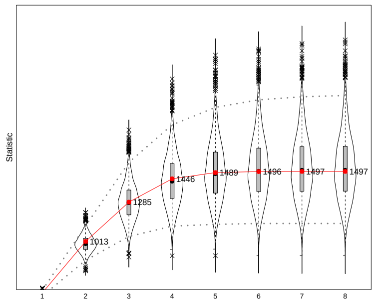
Indegrees



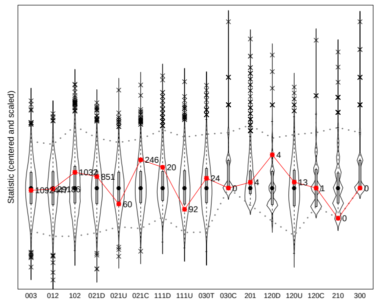
Outdegrees



Geodesic



Triad Census



X-axis: P-value obtained by the Monte Carlo Mahalanobis Distance Test proposed by **?**, testing null hypothesis that auxiliary statistics of observe data is distributed according to plot.

Y-axis: Value of auxiliary statistic (indegree, outdegree, geodesic distance, triad census). Solid red line the observed values equal auxiliary statistic.

“Violin plots” show simulated value of statistic as kernel density estimate and box plot of 95% interval.

Paper D

Determinants of Cross-border Venture Capital Investments in Emerging and Developed Economies: The Effects of Relational and Institutional Trust

Daniel S. Hain[†], Sofia A. Johan[⋆ψ], Daojuan Wang[†]
[†] *IKE, Department of Business and Management, Aalborg University, DK*
[⋆] *York University - Schulich School of Business, Toronto, CN*
[ψ] *University of Tilburg - Tilburg Law and Economics Centre, Tilburg, NE*

The paper has been published (online first) in the
Journal of Business Ethics

The layout has been revised, and a preface not included in the original article has been added.

Abstract

Frequent and open interaction between venture capitalists (VCs) and entrepreneurs is necessary for venture capital investments to occur. Increasingly, these investments are made across jurisdictions. The vast majority of these cross-border investments are carried out in a syndicate of two or more VCs, indicating the effects of intra-industry networks needing further analysis. Using China as a model, we provide a novel multidimensional framework to explain cross-border investments in innovative ventures across developed and emerging economies. By analyzing a unique international dataset, we examine worldwide venture capital investment flows from 2000-2012 and consider the effects of geographical, cultural, and institutional proximity as well as institutional and relational trust. We find trust to mitigate the negative effects of geographical and cultural distance; where institutional trust is more relevant for investments in emerging economies, relational trust is more relevant for investments in developed economies.

JEL Classification: G3, K4, D81

Keywords: Venture capital, institutional trust, relational trust, corruption, China, syndication, emerging economies

Preface

Owing to the increased techno-economic opportunities within knowledge-based economies (Foray and Lundvall, 1996), going hand in hand with the strongly felt uncertainties of scientific and technological innovation (Dosi, 1982, 1988), specialized financial intermediaries dealing with these challenges emerged during the last decades. Venture capitalists (VCs) are a classical - but not the only - example of such intermediaries who combine their unique blend of technological and financial expertise to provide both financial and managerial support for entrepreneurs in innovative ventures. It has been established by extant research that such specialized “innovation investors” not only promote innovative activities (Kortum and Lerner, 1998, 2000; Samila and Sorenson, 2010, 2011), but they also provide additional value-added support to enable innovative products or services to be rapidly brought to market (Black and Gilson, 1998; Bygrave and Timmons, 1992), thereby influencing rate as well as direction of technological change.

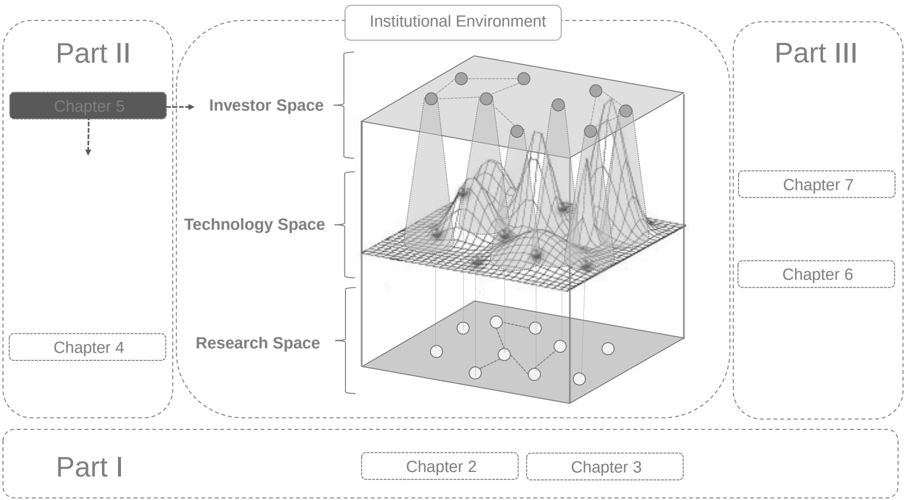
In a connected world where capital as well knowledge is dispersed around the globe, such investments in innovative and entrepreneurial ventures increasingly are made across borders and jurisdictions, in locations with cultural norms, market dynamics and business practices quite distant from the investors local markets. Not surprising, attracting such foreign investments and thereby taping in global pools of capital and knowledge has become an integral goal of recent innovation-related public policies (Beck et al., 2008; Kortum and Lerner, 2000), yet with widely varying outcomes (Cumming, 2010b, 2011). Successful examples who succeeded in the development of a vibrant venture capital industry from scratch are often attributed to network-based strategies, encouraging cooperation between local and foreign investors (Avnimelech et al., 2006; Xiao, 2002).

In this chapter, my co-authors Sofia Johan and Daojuan Wang and I analyze how venture capitalists mitigate information deficits associated with investments over long geographical, institutional and cultural distance by mobilizing knowledge and capabilities of partners within their formal and informal network of informants (Casamatta and Haritchabalet, 2007; Fiet, 1995a). While based on micro-level actions of investors, we mostly focus on macro-level outcomes on country and country-dyad level, in particular we aim to explain the amount of bilateral flows of equity (VC) investments in innovative ventures. We further contrast cross-border venture capital investments in developed and emerging economies, as many emerging economies have been actively supporting their own venture capital markets pursuant to the perceived success of VC contribution to innovation in more developed jurisdictions (Bruton et al., 2004, 2005). These same economies are seeking not only to attract foreign funds but more specifically foreign expertise as it is thought that not only would local entrepreneurs benefit from specialist VC skills, but also that local VCs would benefit from the transfer of knowledge from the more sophisticated foreign venture capitalists. However, underdeveloped investor and property protection, high cultural distance, diverging business ethics and practices, and the perception of corruption in certain jurisdictions are obstacles to the development of these markets.

Incomplete and asymmetric information issues of innovation finance are a – if not the – main guiding topic of my Ph.D. thesis. In this chapter I empirically investigate how investors adjust their strategies to minimize asymmetries, and how these micro-choices manifest in macro-outcomes. Claiming geographical, institutional and cultural distance apparent in most cross-border transactions to be a major obstacle for investments in innovation and technological change, we identify how they can be mitigated by the investors cooperation strategies, and how they differ given the institutional setup of host and target country. I thereby also demonstrate the importance of explicitly taking the institutional context of innovation investments into account, which greatly impacts their quantity as well as quality. In the guiding framework of this Ph.D. thesis, it primarily focuses on network dynamics within the investor space, but also links to the associated technological change of investments as an outcome of these dynamics.

The origins of this paper reach back to my master-thesis, where I also conducted research on cross-border venture capital syndication networks with roughly the same dataset. In its current framing, it was firstly presented at the "UK IRC Early Career Researchers Workshop" 2013 at the University of Cambridge. Since it has been presented at numerous internal and external research seminars, such as the IKE seminar series at Aalborg University and the IDEOS workshop 2013 in Marburg. Latest, it has been presented at the "JBE special issue conference on Business Ethics in Greater China" 2014 in Tibet. Currently, it has been accepted for publication in the corresponding special issue of the "Journal of Business Ethics".

Fig. D.1: Positioning the paper in the theoretical framework



1 Introduction

Venture capitalists (VCs) are specialized financial intermediaries who combine their unique blend of technological competence and financial skills, to provide both financial and managerial support for entrepreneurs in innovative ventures. It has been established by extant research that VCs not only promote innovative activities (Kortum and Lerner, 1998, 2000; Samila and Sorenson, 2010, 2011), but they also provide additional value-added support to enable innovative products or services to be rapidly brought to market (Black and Gilson, 1998; Bygrave and Timmons, 1992). It is not surprising, therefore, that the creation of flourishing venture capital markets has become an integral goal of recent innovation-related public policies in many developed and emerging economies (Beck et al., 2008; Cumming, 2006; Kortum and Lerner, 2000). Although some initiatives have reached their goals, many such policies have not been found to be successful (Cumming, 2003, 2010a).

While research has determined varied reasons for such failures, we believe that one of the main reasons for the lack of success in encouraging venture capital investment is local bias. Local bias has long been considered inherent in financial intermediary activity, as financial intermediaries feel a strong need for spatial proximity and rely heavily on local expertise (Coval and Moskowitz, 1999, 2001; French and Poterba, 1991; Parwada, 2008) to mitigate agency problems. Local bias is, thus, a significant hurdle to breach as markets seek to accelerate development by tapping foreign sources of knowledge and capital (Avnimelech et al., 2006). Local bias can be even more significant for venture capital, as investment in innovative activities involves considerable uncertainty and is characterized by asymmetric information at the outset and agency problems during the investment process.

Frequent and open interaction between investor and investee within close proximity appears necessary for these investments to succeed (Cumming and Dai, 2010; Engel and Keilbach, 2007; Sapienza, 1992; Sapienza et al., 1996). A new, growing body of literature, however, suggests a paradigm shift towards a more globally distributed venture capital investment pattern (Baygan and Freudenberg, 2000; Guler and Guillén, 2005, 2010; Kendall and Aizenman, 2012; Wright et al., 2005). This paradigm shift is not only of interest to governments seeking to further develop local venture capital markets by attracting both foreign funds and expertise; researchers, too, have an interest in deciphering this changing paradigm (Avnimelech et al., 2006; Bruton et al., 2004, 2008, 2005), as this suggests well-recognized institutional challenges that seem to have been surmounted for cross-border investments - such as underdeveloped investor and property protection (Peng, 2001), high cultural distance, diverging business ethics and practices (Ahlstrom and Bruton, 2006; Dai and Nahata, 2013), and the perception of corruption in certain jurisdictions (Johan and Najar, 2010). One possible explanation catching the attention of researchers is network effects, specifically the growing tendency for foreign VCs to team up in a syndicate with domestic partners to take advantage of their local expertise and to ensure interaction (Dai and Nahata, 2013; Manigart et al., 2002; Nahata et al., 2013). In this paper, we analyze these network effects and their effect on local bias.

An example of a jurisdiction that has benefited from this paradigm shift is China. China's institutional environment encompasses the above mentioned weaknesses and has at times been called "peculiar" (Bruton and Ahlstrom, 2003; Lu et al., 2013; Tan and Tan, 2005). In addition, with regard to institutional trust, which we take to indicate overall trust in the institutional structure and the honest behavior of citizens in a particular country, China ranks particularly low. However, China has been able to not only build a venture capital market from scratch since 1984 (Xiao, 2002) but has been able to develop it to the success it possesses today. China's success at attracting both local and foreign venture capital has been previously attributed to network-based strategies, also known as a form of relational trust, or guanxi, utilized by market participants (Peng, 2003; Pukthuanthong and Walker, 2007; Su et al., 2007). In this paper, we posit that while institutional trust is not attached to a particular relationship, it serves to ease the way in establishing one, as it mitigates the effects of lack of proximity in cross-border investments. As the relationship is established and relational trust is built, the perceived uncertainty of the investments gradually declines while a mutual understanding develops, and both parties move towards a more symmetric information base. Thus, even in the absence of relational trust, we expect countries with high institutional trust to hold higher venture capital inflows and syndication activities, despite potential social and geographical distance. We refer to China as a model for this paper, as we seek to augment existing research in the pattern of international alliances and syndicates in the venture capital industry. We believe that for a more thorough understanding of the balance between institutional factors and network effects, our research must take into account numerous jurisdictions, both developed and emerging, for legal, lingual, political, and market capitalization and cultural differences to be appropriately analyzed. More importantly, few jurisdictions possess such pronounced institutional characteristics as China.

We begin by acknowledging that although geographical and cultural norms may differ across countries, one thing that remains unchanged is the secretive and high-risk nature of nascent, innovative start-up firms. To mitigate the adverse selection risk in start-up investment, frequent, persistent, and open exchange of both codified and tacit information (Polanyi, 1966) is necessary between the creators of the innovation and their cross-border financiers (Cumming, 2006). The frequency, openness, and quality of the social exchange among parties is naturally dependent upon proximity. For the purposes of this paper, we use several measures to analyze the effect of geographic, institutional, lingual, and cultural proximity, along with corruption levels and political instability.

Along this process of exchanging both codified and tacit information among market participants, institutional trust must be established; as the number of interactions increase, relational trust also increases. We recognize that institutional and relational trust differ in their influence, depending on the participant composition of the investments (foreign only vs. foreign and domestic VCs) and the institutional setup of the destination country (developed vs. emerging economy).

We find that the higher the geographical and cultural distance, the lower the likelihood of cross-border investment. High-market capitalization and low corruption levels in the destination country encourage VCs to overcome local bias and consider an investment in that country. When focusing on investments in emerging economies, we also find a particularly strong negative effect on corruption. Venture capital flow does appear to move from high-growth countries to low-growth countries; therefore, it appears that VCs are willing to take on the higher risk of investment in emerging economies. Our findings suggest that VCs mitigate the investment risk with social exchange among a syndicate comprising at least one local VC to overcome lack of proximity. Our findings also suggest that relational trust helps overcome high geographical, cultural, and institutional distance. We find, however, that institutional trust has a more positive impact on cross-border venture capital flows from developed to emerging economies. This may be because VCs may prefer to rely on their familiarity with established institutional factors in making investment decisions and do not necessarily view relational trust as a substitute for institutional trust. Sophisticated VCs with sectoral experience, for example, may believe they are sufficiently capable to assess the viability of an innovative firm. The viability of investing in a certain jurisdiction with the institutional information they have gathered ex-ante and is not reliant on the information gathered from social exchange with less sophisticated local VCs ex-post, though such information may still mitigate investment risk. Another explanation for institutional trust having more of an impact on cross-border venture capital flow from developed to emerging markets is that VCs from the developed economies would prefer not to dilute their reputational capital by investing with less reputable VCs from emerging economies.

The remainder of the paper is structured as follows: In section 2, we provide a theoretical background, review seminal academic work, and develop a socio-economic framework of cross- border venture capital. Empirical tests are discussed in section 3. Section 4 concludes and derives implications for practitioners, policy-makers, and scholars.

2 Theory and Hypothesis

Prior research has sought to explain the patterns of global venture capital allocation with reference to general macroeconomic conditions. Most of the research concludes that certain characteristics, such as high market capitalization (Black and Gilson, 1998), growth rates (Romain and Van Pottelsberghe, 2004a,b), and sophisticated institutions which ensure the protection of investors rights (Guler and Guillén, 2005, 2010; La Porta et al., 1998, 2000, 1997) create favorable investment conditions that ultimately lead to higher cross-border venture capital. While such determinants that capture different aspects of a country's aggregated economic activity can somehow trigger cross-border venture capital flows, we believe they are somewhat limited in explanatory power. In particular, they fail to acknowledge the inherent features of innovation, which makes its finance distinctively challenging (Hall, 2010; Hall and Lerner, 2009). Innovation, by definition, is the creation of somewhat qualitatively different, novel, and unproven products, processes, or business models. The financing of innovation is surrounded by uncertainty, stemming mainly from incomplete information and a limited ability to interpret incomplete information (Knight, 1921). Such incomplete information leads to high adverse selection risks borne by the financier of innovation. Furthermore, the entrepreneurs or innovators usually have more complete information than the venture capital investors (Cumming, 2006). In the case of start-ups, this problem is further amplified as historical data enabling the projection of future performance are neither available for the applied technology nor the firm (Berger and Frame, 2007; Berger and Udell, 2002; Freel, 2007). Unlike other forms of traditional financing, such as bank or public market financing, the quality of both quantitative and qualitative information necessary to evaluate the financing of an innovative start-up firm is so poor that VCs have to resort to spatial proximity and local expertise or knowledge to gather the information required to mitigate their significant financial risk (Coval and Moskowitz, 1999, 2001; French and Poterba, 1991). This information gathering may be significantly more challenging in cross-border investments, especially between developed and emerging economies; therefore, local bias in inevitable.

Polanyi (1966) classifies human knowledge as consisting of codified (or explicit) and tacit elements. Where codified elements are easily transmittable using a standardized formal and systematic language, such as mathematics, tacit elements are context-dependent and personal, hard to formalize and transmit over distance, necessitating face-to-face and interpersonal interaction (Arrow, 1962; Von Hippel, 1994). Information required to mitigate traditional financial risk and ascertain return optimization, such as balance sheets or performance records, are of a codified nature and readily available. We noted earlier that for venture start-ups, such information is rarely available. Even where such information is available and codified, with cross-border investments, the information may not necessarily be easily decipherable, not completely understood, as though in a different language or subject to an unfamiliar institutional context. In addition, tacit knowledge includes the personal characteristics of an entrepreneur or an understanding of novel product concepts; tacit knowledge is not readily available and gradually unfolds in a timely process of interaction between individuals. Hence, the very act of gathering tacit information requires the establishment of a relationship and continuous interaction between (co-) investors and entrepreneurs. As a consequence, we suggest concepts usually used to explain the emergence and performance of interpersonal and organizational relationships to be of high explanatory power when analyzing cross-border VC investments. In particular, we draw from proximity concepts (Boschma and Frenken, 2010; Boschma, 2005) and theories on institutional and relational trust.

We know that spatial proximity and local expertise or knowledge is used by VCs to identify the existence of innovative ventures and to gather the information required to mitigate their significant financial risk (Coval and Moskowitz, 1999, 2001; French and Poterba, 1991). We believe that geographical proximity, which indicates the physical distance between the VC and the innovative start-up firm, is necessary for frequent and open interaction between the VC and the entrepreneur (Cumming and Johan, 2007). Open interaction facilitates the gathering of both codified and tacit information required by VCs to determine the existence of innovative ideas and the viability of an investment in an innovative venture. We know that geographic proximity is especially important in the pre-deal selection, due-diligence, as well as the post-deal monitoring and value-adding phase of a venture investment (Cumming and Dai, 2010; Davila et al., 2003; Engel and Keilbach, 2007; Jääskeläinen et al., 2006; Mäkelä and Maula, 2008; Sapienza et al., 1996). This is mainly because the advice and monitoring provided to the startup firm is made at board or management meetings at the firm office; therefore, geographic proximity allows VCs to easily travel to the firm office within the VC's constrained time limitations (Cumming and Johan, 2006b). Note that a VC would have more than one investee firm in his portfolio; traveling between large geographic distances would therefore affect the frequency of interaction between the entrepreneur and the VC.

In addition to geographic proximity, institutional similarities and differences in legal systems are also likely to influence cross-border VC investment activity. Venture capitalists do their best to mitigate the agency costs of venture investment (Avnimelech et al., 2006; Fiet, 1995a,b, 1996; Shepherd and Zacharakis, 2001) with the use of effective contracts and governance structures (Cumming and Johan, 2013). The differences in legal systems increase information asymmetries, the cost (legal and contractual), and the risk of investment. Seminal work by La Porta et al. (1998, 2000, 1997) has shown that law quality can significantly affect the costs and benefits associated with monitoring the entrepreneur. Briefly stated, more efficient legal systems lower the costs associated with monitoring the entrepreneur and, thereby, increase the scope for the VC to maximize private benefits or profits. More dissimilar and inefficient legal systems are known to impede the ability of a VC to finance firms and, thus, hamper the rate of investment. In addition to legality differences, other institutional factors - including levels of corruption and political instability - will also affect investment (Davis and Ruhe, 2003; Johan et al., 2013; Johan and Najar, 2010). Furthermore, sharing a common language may be a necessary precondition for knowledge transfer. We take into consideration lingual distance, as we believe that codified elements of information are worthless if indecipherable due to lingual distance.

Cultural dimension is also of high importance when explaining how business is accomplished in general (Hofstede and Bond, 1984; Hofstede et al., 2010). Cultural distance, another proximity measure, can be associated with diverging values, business ethics, and codes of conduct. As recent studies show, countries with higher cultural distance show higher mistrust (Guiso et al., 2008), and discourage risk sharing (Giannetti and Yafeh, 2012) among potential investors. Since the selection, evaluation, monitoring, and management support of VC investments necessarily requires frequent and open interactions between involved participants, high cultural distance can be expected to represent a major obstacle for cross-border investments. Tacit elements of information gathering are context dependent, and cultural distance may make this significantly more difficult among parties.

To overcome the limitations of proximity, VCs seeking to cross borders when investing in innovative ventures do so within syndicates. Some choose to syndicate with local VCs, as cross-border syndicates between domestic and foreign investors are said to reduce transaction costs (Tykvová and Schertler, 2008) and bridge high cultural and institutional distance (Dai and Nahata, 2013; Tykvová and Schertler, 2013).

We, therefore, hypothesize as follows:

Hypothesis 4

a: Geographical, cultural and institutional distance negatively affect venture capital investment activity between countries.

b: The negative effects of geographical, cultural and institutional distance negatively are less pronounced in cross border investments syndicated with a domestic VC.

We noted in an earlier section that VCs do their best to mitigate the agency costs of venture investment with the use of effective contracts and governance structures to protect themselves against opportunistic behavior (Avnimelech et al., 2006; Cumming and Johan, 2013; Fiet, 1995a,b; Shepherd and Zacharakis, 2001). Such risks, however, can never be completely eliminated (Bergemann and Hege, 1998; Cumming and Johan, 2013; Farmer and Winter, 1986; Sahlman, 1990). It is especially difficult to mitigate such agency costs with the use of contracts and governance structures in view of less efficient laws and corporate structures across different borders (Cumming and Johan, 2006a; La Porta et al., 1998, 2000, 1997). In situations where residual uncertainty stemming from incomplete contracts and asymmetric information cannot be eliminated through contracts and protection through formal institutions, trust among parties is imperative in facilitating investment activities, which is particularly true when it comes to investment in innovation (Nooteboom, 2006). For the purposes of this paper, we distinguish between institutional and relational trust (Rousseau et al., 1998). Institutional trust is present ex-ante to the interaction and refers to the trust in the institutional environment, which includes institutional factors related to the legal framework and its enforceability as well as soft factors, such as a society's attitude to behave fairly and honestly. In contrast, relational trust ex-post unfolds gradually through repeated interactions over time (Blau, 1964; McAllister, 1995).

We argue that institutional and relational trust are both very important in cross-border venture capital deals, but they differ in their influence, depending on the participant composition (foreign only vs. foreign and domestic VCs) of the investments and the institutional setup of the destination country (developed vs. emerging economy). Our arguments are based on prior research, which finds that in high-trust societies, parties must spend fewer resources to protect themselves against opportunistic behavior. Parties making investment and production decisions more focused on the long run have higher incentives and return on the accumulation of human capital (Knack and Keefer, 1997) and are more likely to share knowledge (Dovey, 2009) and participate in open innovation projects (Nooteboom, 2006). Trust between countries also positively influences their economic exchange in terms of stock market investments (Guiso et al., 2008), foreign direct investments, and bilateral trade (Guiso et al., 2009).

Recently Duffner et al. (2009) and Bottazzi et al. (2011) also provide empirical evidence showing a strong statistical and economic significance of trust on venture capital investments, reporting generalized and personalized trust ex-ante to reduce doubts regarding an investment decision and ex-post to provide a good foundation for efficient and effective communication and interaction between them. For stand-alone foreign investments, we assume that the VC and the entrepreneur maintain no relationship prior to the investment; thus, they have no way to build up endogenous forms of trust. Here, the role of institutional trust ex-ante is of significant importance, providing the foundation for building up a critical mass of initial trust to enter a relationship involving proximity. Once the relationship is initiated, the parties build up relational trust, resulting from frequent and open information sharing. We note, however, that relational trust ex-post unfolds gradually through repeated interactions over time, and the extent of proximity will affect the absorption rate of social exchange; therefore, for investments with greater distance between developed and emerging economies, for example, institutional trust would play a greater role at the outset.

The relationship between the entrepreneur and a VC would differ from one VC to another. The VC community is small, and reputation is key (Hsu, 2004; Nahata, 2008; Nahata et al., 2013). Information regarding unprofessional or dishonest behavior diffuses quickly and influences a VC's future deal flow opportunity substantially in quantity and quality. As a consequence, VCs theoretically have an incentive to consistently behave honestly and fairly with their investees and syndicates in order to maintain or build up their valuable reputation. However, for cross-border relationships, proximity may temper the dissemination of reputational quality. Also, the quality of VCs from emerging economies may not be up to par in relation to VCs from more developed jurisdictions (Nahata et al., 2013). However, VCs working as a syndicate or a network are able to build up, over time, persistent long-term relationships. As a result, relational trust eventually emerges between former syndication partners, lowering the uncertainty when joining further investment invitations with the same partners. Still, we expect this effect due to differences in reputation effects and experience/quality to be of lower magnitude for foreign-domestic syndicates in emerging economies. Thus, we hypothesize as follows:

Hypothesis 5

a: Institutional and relational trust positively affects bilateral venture capital investment activity and diminishes the negative effects of geographical, social, and institutional distance.

b: The positive effects of institutional trust appear stronger for investments in emerging compared with developed economies.

c: The positive effects of institutional trust appears weaker for cross-border investments syndicated with domestic VCs.

d: The positive effects of relational trust appear weaker for investments in emerging compared with developed economies.

3 Empirical Setting

3.1 Variables & Data

In the following section, we briefly describe our data sources, empirical model, employed variables, and their construction. Supplementary, table D.10 in the appendix provides an exhaustive overview on all variables, their composition and source. In the following, the subscript i identifies the source country (SC), j the destination country (DC). $\Delta_{i,j}$ labels the variable to be the destination country's j minus the source country's i corresponding variable value.

Data on Cross-border Venture Capital Deals

For our empirical analyses, we draw from Bureau van Dijk's Zephyr databases on global equity investments.[1] We include all venture capital identified deals between 1998 and 2013, where the first two years are only used to create lagged variables of investment activities. To minimize noise caused by one-off investments, we exclude investments of VCs that carried out only five or less investments during the final observation period, 2000-2013. We aggregate these deals on the level of the dyad between source and destination country. In deals with investors from multiple source countries, the deal is accounted once for every involved country-dyad, independent of the number of investors. For example, if two French VCs and one German VC invest in syndicate in an Irish portfolio firm, the country dyads FR-IE and DE-IE both get one additional count for this deal. Our final dataset contains 30,650 deals, of which 11,665 cross-national borders; 1,555 VCs in 8.665 unique portfolio companies located in 37 countries - 22 developed and 15 emerging economies - carry out these cross-border deals.

To get a first impression on global VC investment activity, table D.8 in the appendix provides further information on domestic venture capital investments, cross-border inflows, and outflows per country for the top quantile (in terms of investment activity) of countries. For the development of VC activity over time, consider table D.9. Finally, D.11 sets out a matrix of venture capital investments between country pairs, where we show the activity between the in terms of VC activity.

Dependent Variables

In most related studies, venture capital flows between country dyads and is measured by either counting the number of investments or their monetary value, which is strongly influenced by the size of the countries under study. All else being equal, this amount is obviously expected to be higher between large economies, and *vice versa*. To take the gravity effect of economic size into account (c.f. e.g. Feenstra et al., 2005; Krugman, 1980; Pöyhönen, 1963; Tinbergen, 1962), we construct our dependent variable as a measure of venture capital flow propensity.

$$VC\ prop^t_{i \to j} = \frac{VCflow^t_{i \to j} / VCinvest^t_i}{GDP^t_i / GDP^t_j} \tag{D.1}$$

[1]For a detailed description of the Zephyr database and its positive value for cross-border venture capital research, see Schertler and Tykvová (2009, 2010)

The numerator represents the share of dyadic investments from the source country for all the venture capital investments in the destination country; the denominator represents the ratio between the source and destination country's GDP. For the sake of comparison and robustness, we also used the number of annual deal counts ($VC\ inv^{t}_{i \to j}$) as a dependent variable for an alternative model.

Independent Variables

Geographic Distance We follow Mayer and Zignago (2011) by measuring $geographical distance$ as the population density adjusted for distance in kilometers between a country dyad, where we generally expect a negative effect on venture capital investment activity. However, with increasing geographical distance, investors are able to substitute means of transportation (e.g., car, train, airplane) and communication, leading to a non-linear increase of investment obstacles in geographical space (Sorenson and Stuart, 2001). To account for this, we use the logarithmic transformation of geographical distance.

Cultural Distance To measure *cultural distance*, we calculate the distance between countries over Hofstede's (2010) four cultural dimensions (power distance, individualism, masculinity, uncertainty avoidance), following the approach of Kogut and Singh (1988):

$$dist\ cult_{i,j} = \frac{\sum_{u=1}^{4} \frac{I_j^u - I_i^{u\ 2}}{var(I^u)}}{4} \tag{D.2}$$

Lingual Distance In addition, we include a dummy variable provided by Melitz and Toubal (2012) indicating that the countries share a common language ($same\ lang_{i,j}$) spoken by at least 10% of the population in both countries. The lack of a common language might very well represent an obstacle in both the communication of both codified and tacit information between VCs and investee firms and between entrepreneurs and other officials in the destination country.

Institutional Distance and Quality of Institutions Venture capitalists investing in countries with different institutional settings are confronted with unfamiliar explicit and implicit "rules of the game" (North, 1990), codes of conduct, and general business practices and ethics. Institutional distance is, thus, commonly regarded as a major obstacle for cross-border venture capital investments (Guler and Guillén, 2010; Megginson, 2004). To analyze the effect of *institutionaldistance*, we employ a set of different measures.

First, a dummy variable is implemented indicating the country's legal system, based on different law traditions ($same\ legal_{i,j}$), as classified by La Porta et al. (1998). Legal differences are associated with increased ex-ante information costs and decreased ex-post capabilities of adding value and are, thus, expected to negatively affect investment activities between country dyads. The level of corruption in the destination country represents another institutional facet likely to affect cross-border venture capital flows, particularly in developing economies which tend to have less-developed, formal institutional structures (Peng, 2000). We, therefore, include the Corruption Perception Index (cpi_j^t) provided by Transparency International in our set of independent variables. The CPI reflects the view of a panel of country experts on how corrupt the public sector of the corresponding country is perceived. The CPI is considered one of the most reliable measures of corruption around the world (Wilhelm, 2002). Generally, we expect corruption to negatively affect the amount of cross-border venture capital inflows. However, in countries with rigid and ineffective formal institutions, market-driven corruption can also be a means to grease the wheel and get business done (Huntington and Fukuyama, 2006; Leff, 1964; Levy, 2007; Nielsen, 2003). Learning to deal with corruption might turn out to be a key capability in such settings. Therefore, we also include the differential between the destination and source country's CPI (Δcpi_{j-i}^t) in our empirical tests. To account for the effects of political instability and the associated increase of uncertainty in countries with highly unstable political regimes, we also employ the measure provided by Kaufmann et al. (2010), which captures perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means ($inst\ stab_j^t$).

Institutional Trust *Institutional trust* is the perception that other people can generally be considered as trustworthy. Institutional trust represents a commonly used measurement for social capital and relational embeddedness, and it is said to strongly impact economic activity in (e.g. Dovey, 2009; Guiso et al., 2008; Knack and Keefer, 1997) , as well as between, countries (Guiso et al., 2008), particularly in transactions characterized by high uncertainty (Nooteboom, 2006). To analyze the impact of this institutional facet on cross-border venture capital flows, we employ a common measure for institutional trust ($trust_j$) in economic analysis (e.g. Beugelsdijk, 2006; Knack and Keefer, 1997) provided by the Survey (2009).[2]

We expect high-trust destination countries to receive a higher share of cross-border venture capital investments. Comparing the WWS in-country measure with the measure of bilateral trust provided by the Eurobarometer (2011)[3] reveals a high correlation between a country's internal generalized trust and the trust received by other countries. Therefore, we also interpret a country's generalized trust as an approximation for the level of trust received by the source country. Trust in the society as a whole is also cause and consequence of trust in the quality of political and economic institutions. Hence, it is not surprising that the WWS measure of generalized trust, in our sample as well as other studies, strongly correlates with measures of institutional quality, such as indices for political stability, property right protection, freedom of press and speech, and quality of the legal system.

Relational Trust In order to analyze the possible effect on syndication that domestic venture capitalists might play in bridging geographical, institutional, and cultural distance (Dai and Nahata, 2013; Tykvová and Schertler, 2013), harnessing synergies of complementary resource bases (Chemmanur et al., 2011), and providing credible signals on the portfolio company's quality (Mäkelä and Maula, 2008), we also include a variable ($VC\ synd^t_{i \to j}$) representing the share of investments carried out in syndication with domestic investors to all investments of the source i in the destination country j. While cross-border investments of foreign VCs directly into domestic investee companies may not necessarily necessitate a former relationship between them, for syndicated investments between domestic and foreign VCs, it is very well likely that not only will the participants already know each other, either through prior joint investments, shared contacts, or reputation, but that there sufficient, open, and persistent lines of communication exist. Thus, for our analysis, we interpret ($VC\ synd^t_{i \to j}$) as a first approximation of potential relational trust between country dyads.

Trade Flow To account for the intensity of economic relationships between countries we use a standard measures from the trade literature: The product

[2]Since the different waves of the survey do not always cover all countries, in some cases, survey results were used from older waves between 1995 and 2000. The correlation coefficient across the different waves always sits above 90 percent, which indicates that the phenomenon of trust is somewhat persistent over time.

[3]Unfortunately, this measure is only available for a subset of European countries and, therefore, could not be used against the background of our analysis.

of last year's export from country i to j and j to i, divided by the products of their GDP:

$$trade_{i \to j}^{t-1} = \frac{export_{i \to j}^{t-1} * export_{j \to i}^{t-1}}{gdp_i^{t-1} * gdp_j^{t-1}} \tag{D.3}$$

Control Variables Furthermore, we control for the following country and country-dyad specific characteristics. The growth-rate of the destination country's GDP ($growth_j^{t-1}$) reflects the tendency to invest in countries with high economic growth and the differential between the growth of destination and source country. A vivid stock market represents a profitable exit option for venture capital investment and is said to have a positive effect on venture capital activity (Black and Gilson, 1998; Gompers et al., 2008), which we take into account by incorporating control variables for the destination country's ratio of market capitalization ($capitalization_j^{t-1}$) and stocks traded capitalization ($stocks_j^{t-1}$) to its GDP. Additional to the characteristics of the destination country, we also include directional controls for the differences between the destination and source country ($\Delta growth_{j-i}^{t-1}$, $\Delta capitalization_{j-i}^{t-1}$, $\Delta stocks_{j-i}^{t-1}$). For the sake of clarity, and to avoid very high differences in the order of magnitude of the coefficients, we have rescaled all control variables in the country dyad by dividing by their maximum, resulting in a range [0,1].

Foreign VC Characteristics For an additional model analyzing the constellation of cross-border venture capital deals, we also include a set of variables indicating the highest prior investment experience of the foreign VCs in the same sector ($expsector_{max(k)}^t$), the destination country ($expcountry_{max(k)}^t$), and prior investments in the current portfolio company itself ($exp\ target_{max(k)}^t$).

3.2 Descriptive Statistics

Table D.1 provides general descriptive statistics on country dyad, and table D.2 on deal level.

The correlation matrix of our macro-level analysis provided in table D.3 shows that, generally, venture capital, in absolute ($VC_{i \to j}^t$) as well as in relative ($VC\ prop_{i \to j}^t$) terms, tends to flow towards destination countries with low cultural and geographical distance and low corruption and high trust, as one might expect. These variables are also associated with a higher share of syndicated investments between source and destination country ($VC\ synd_{i \to j}^t$),

Table D.1: Descriptive Statistics, Country Dyad Level

Variable	N	Mean	Std. Dev.	Min	max
		Dependent			
VC count$^{t}_{i\to j}$	70,571	0.151	1.943	0.000	104.000
VC prop$^{t}_{i\to j}$	70,571	0.006	0.158	0.000	29.920
		Distance			
dist geo$_{i,j}$	68,597	8.586	0.918	3.835	9.886
dist cult$_{i,j}$	36,414	0.060	0.023	0.006	0.150
same legal$_{i,j}$	70,571	0.225	0.418	0.000	1.000
same lang$_{i,j}$	68,597	0.146	0.353	0.000	1.000
		Trust & Relationship			
trust$_{j}$	63,711	0.063	0.314	-0.427	1.000
VC synd$^{t}_{i\to j}$	70,571	0.015	0.113	0.000	1.000
trade$^{t}_{i,j}$*	66,226	0.559	0.227	0.150	1.000
		Institutions & Relational Trust			
cpi$^{t*}_{j}$	66,226	0.559	0.227	0.150	1.000
inst stab$^{t}_{j}$	68,605	0.260	0.921	-2.812	1.668
		Controls			
gdp$^{t-1*}_{j}$	68,586	0.045	0.118	0.000	1.000
gdp cap$^{t-1*}_{j}$	68,587	0.178	0.180	0.002	1.000
gdp growth$^{t-1}_{j}$	68,516	0.893	0.103	0.000	1.000
capitalization$^{t-1}_{j}$	66,570	0.110	0.115	0.000	1.000
stocks$^{t-1}_{j}$	66,640	0.062	0.102	0.000	1.000

This table presents descriptive statistics of our main variables for the models on country dyad level.
The source country is denoted with subscript i, the destination country with j
* indicates the variable is normalized(divided by maximum, hence [0,1]).

Table D.2: Descriptive Statistics – Cross-Border Venture Capital Deals

Variable	N	Mean	Std. Dev.	Min	max
		Dependent			
deal_host	7,349	0.599	0.490	0.000	1.000
		Destination Country			
gdp_j^t	7,346	0.438	0.400	0.000	1.000
gdp growth_j^t	7,346	2.491	2.757	-14.072	14.781
$\text{capitalization}_j^t$	7,344	107.068	46.252	-19.815	549.423
cpi_j^t	7,340	0.725	0.146	0.17	1.000
trust_j	7331	0.885	0.821	-1.478	3.459
		Dyad			
$\text{dist geo}_{mean(i,j)}$	7,324	8.158	1.144	5.087	9.833
$\text{dist cult}_{mean(i,j)}$	7,251	0.040	0.024	0.006	0.130
$\text{same legal}_{max(i,j)}$	7,325	0.541	0.498	0.000	1.000
$\text{same lang}_{max(i,j)}$	7,324	0.540	0.498	0.000	1.000
		Acquiring foreign VCs			
$\text{exp sector}_{max(k)}^t$	7,349	21.607	38.652	1.000	270.000
$\text{exp country}_{max(k)}^t$	7,349	9.106	14.435	1.000	111.000
$\text{exp target}_{max(k)}^t$	7,349	1.262	0.545	1.000	5.000

This table presents descriptive statistics of our main variables for the models on country dyad level.
The source country is denoted with subscript i, the destination country with j
* indicates the variable is normalized(divided by maximum, hence [0,1]).

contrary to the idea that VCs use syndication with domestic partners particularly as a means of dealing with high distance and local uncertainty. Interestingly, there is no strong correlation observable between the institutional and geographical *per se*. The remaining correlations between variables are as expected, overall, and in a reasonable scale. The only exceptions are the high correlations between $trust_j$, $inst\ stab_j^t$ and cpi_j^t, and between $capitalization_j^{t-1}$ and $stocks_j^{t-1}$. Since this set of variables measure different facets of the same phenomenon, to some extent, high correlation can be expected.[4]

Table D.4 provides the correlation matrix for the set of regressions at the deal level. Worth mentioning is that, in contrast to the macro level models, the variables for institutional, cultural, and legal distance strongly correlate. Again, by sequentially adding these variables in different combinations in the model-building phase, we ensure the stability of our models and the robustness of the results.

[4]Since the models provide stable results, and colinearity diagnostic statistics such as the variance inflation factor indicate no worrisome instability, we decided to use these variables jointly. However, we first ran a set of unreported regressions, in which we sequentially add these variables in different combinations and observe changes in coefficient values and variance.

Table D.3: Correlation Matrix – Country Dyad Level

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	$\text{VCt}^t_{i\to j}$	1.0000							
(2)	VC $\text{prop}^t_{i\to j}$	0.2412*	1.0000						
(3)	dist $\text{cult}_{i,j}$	-0.0878*	-0.0503*	1.0000					
(4)	dist $\text{geo}_{i,j}$	-0.0036	-0.0384*	0.1871*	1.0000				
(5)	dist $\text{tech}_{i,j}$	-0.0328*	0.0094	0.0493*	0.0374*	1.0000			
(6)	$\text{trade}^t_{i,j}$	0.0283*	0.0453*	-0.0913*	-0.1258*	0.0049	1.0000		
(7)	same $\text{legal}_{i,j}$	0.0612*	0.0417*	-0.2471*	-0.0806*	0.0064	0.0418*	1.0000	
(8)	same $\text{lang}_{i,j}$	0.1058*	0.0485*	-0.1593*	0.0150	-0.0018	0.1569*	0.2385*	1.0000
(9)	VC $\text{synd}^t_{i\to j}$	0.2059*	0.1641*	-0.1005*	-0.1581*	-0.0613*	0.0477*	0.0574*	0.1452*
(10)	trust_j	0.0283*	0.0304*	0.1531*	-0.0907*	0.0035	0.0115	-0.1168*	0.0008
(11)	cpi^t_j	0.0350*	0.0012	0.0824*	-0.1505*	0.0003	-0.0073	-0.0697*	0.0742*
(12)	gdp growth^t_j	-0.0159	-0.0012	0.0165	0.1068*	-0.0010	0.0322*	-0.0033	0.0234*
(13)	$\text{capitalization}^t_j$	0.0321*	0.0132	0.0308*	0.0456*	-0.0059	0.0687*	-0.0125	0.1422*
(14)	stocks^t_j	0.0882*	0.0581*	0.0377*	0.0219*	-0.0020	0.0599*	-0.0102	0.1308*
(15)	gdp^t_j	0.2465*	0.1402*	-0.0012	0.0761*	0.0076	0.0192*	0.0224*	0.0848*
(16)	inst stab^t_j	0.0013	-0.0132	0.0369*	-0.1783*	-0.0049	-0.0052	-0.0673*	-0.0468*

		(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(9)	VC $\text{synd}^t_{i\to j}$	1.0000							
(10)	trust_j	0.1084*	1.0000						
(11)	cpi^t_j	0.1582*	0.6501*	1.0000					
(12)	gdp growth^t_j	-0.0751*	-0.0967*	-0.2901*	1.0000				
(13)	$\text{capitalization}^t_j$	0.0744*	0.2278*	0.4028*	0.1375*	1.0000			
(14)	stocks^t_j	0.1714*	0.2981*	0.3481*	0.0237*	0.7248*	1.0000		
(15)	gdp^t_j	0.3047*	0.1052*	0.0700*	-0.0786*	0.0641*	0.3500*	1.0000	
(16)	inst stab^t_j	0.0519*	0.5465*	0.7755*	-0.2734*	0.2430*	0.1850*	-0.0280*	1.0000

* indicates $p < 0.001$, two-tailed Pearson correlation

Table D.4: Correlation Matrix – Deal Level

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	deal host								
(2)	gdp_j^t	0.3144*							
(3)	gdp cap_j^t	0.2667*	0.4751*						
(4)	gdp growth_j^t	-0.1386*	-0.1139*	-0.4336*					
(5)	$\text{capitalization}_j^t$	0.1715*	0.3327*	0.3288*	0.0980*				
(6)	cpi_j^t	0.2441*	0.0760*	0.6577*	-0.4051*	0.3978*			
(7)	trust_j	0.0397*	0.1050*	0.2448*	0.1830*	0.1511*	0.2586*		
(8)	$\text{dist geo}_{mean(i,j)}$	-0.0002	0.4607*	-0.0465*	0.1908*	0.1384*	-0.3004*	-0.0316*	
(9)	$\text{dist cult}_{mean(i,j)}$	-0.1749*	-0.1897*	-0.3067*	0.1823*	-0.1970*	-0.3176*	-0.0017	0.1571*
(10)	$\text{same legal}_{max(i,j)}$	0.0931*	0.0681*	0.1173*	-0.0443*	0.1248*	0.1113*	-0.0865*	0.0151
(11)	$\text{same lang}_{max(i,j)}$	0.0699*	0.1082*	0.0995*	-0.003	0.1715*	0.0494*	-0.1603*	0.0991*
(12)	$\text{exp sector}_{max(k)}^t$	-0.0418*	-0.1119*	-0.1242*	0.0096	-0.0970*	-0.0959*	-0.0524*	0.0337*
(13)	$\text{exp country}_{max(k)}^t$	0.1768*	0.3096*	0.0886*	-0.0612*	0.0459*	-0.0093	-0.011	0.0913*
(14)	$\text{exp target}_{max(k)}^t$	0.1577*	0.0512*	0.0838*	-0.0509*	0.0302*	0.0618*	-0.0036	-0.0514*

		(9)	(10)	(11)	(12)	(13)
(10)	$\text{same legal}_{max(i,j)}$	-0.5308*				
(11)	$\text{same lang}_{max(i,j)}$	-0.4955*	0.8125*			
(12)	$\text{exp sector}_{max(k)}^t$	-0.0324*	0.0295	0.0550*		
(13)	$\text{exp country}_{max(k)}^t$	-0.1990*	0.0792*	0.0849*	0.4169*	
(14)	$\text{exp target}_{max(k)}^t$	-0.1093*	0.0747*	0.0722*	0.0942*	0.1871*

* indicates $p < 0.001$, two-tailed Pearson correlation

3.3 Model Specification

Even though the global venture capital investment network has sharply increased during the last decade, compared with international trade flows, which are still rather sparse, only around a quarter of all country dyads show cross-border venture capital investment activity during the observation period. When explanations for these country dyads without investment activity diverge from the model estimating their absolute or relative amount of investment activity, issues of structural zeroes and endogenous selection arise. To deal with potential biases, we apply two-stage estimation techniques in both cases. For the set of GLS regressions, we first fit a probit model, estimating the probability that a country dyad accounts for any investment activity from 1998 until 2013. Following Heckman (1979), we calculate the inverse Mills ratio, and insert it into the GLS model.[5] Since many of our independent variables are time-invariant and our dependent variable construction makes it unlikely to face omitted variable problems (since it already accounts for differences in domestic VC and general economic activity), we deploy a ran-

[5]The results of the first stage of the model accounting for endogeneous selection can be found in table D.12 in the appendix. For robustness check, we also run a random as well as source and destination country fixed effects logit model, where the results all point in the same direction.

dom effect model. Standard procedures such as the Hausman test confirm this choice.

In another model, we are interested in contrasting entry-mode decisions of VCs in foreign-developed and emerging economies. In particular, we are interested in determining which conditions local investors have included in the otherwise foreign investment syndicate. Therefore, with single cross-border venture capital deals as units of observation, we run a simple logit model on the dependent variable, which - if the deal includes not only the foreign VC but also at least one investor with residence in the same country as the investee firm - takes the value of one. To contrast investments in developed economies with the ones in emerging economies, we additionally run this model using only the corresponding sub-sample. To avoid sampling issues, we here calculate the standard errors with the bootstrapping method.

3.4 Results and Discussion

Table D.12 reports the results of this set of GLS random-effect regressions again at the country dyad level where we are aim to contrast the effects of distance and trust on VC investment propensity in deals only consisting of foreign investors vis-à-vis deals also including a domestic investor located in the destination country. We therefore in models 1 and 2 only include foreign-only cross-border investments when constructing our dependent variable ($VC\ prop^t_{i \to j}$), whereas in models 3 and 4, we only include foreign-domestic syndicates.

At first glance, the results lend support to hypothesis 4.a and hypothesis 4.b indicating that VC investment activity is negatively affected by geographical and cultural distance, where the results are less pronounced in the sub sample, including investments only including a domestic syndication partner. Both the magnitude and significance are lower in this sub-sample. To allow for path dependencies in the VC investment pattern, we control for the lagged dependent variable ($VC\ prop^{t-1}_{i \to j}$), which is significant in all settings. $Trade^t_{i \to j}$ shows no statistical significance in all settings.[6]

In Models 2 and 4, we introduce the measure for *institutional trust* in the destination country. As expected by 5.a, institutional trust positively impacts

[6]Alternative measures for bilateral trade, such as unidirectional trade from SC to DC or DC to SC, sum of trade between SC and DC, trade only of goods or services *et cetera* also remain insignificant.

Table D.5: Regression table – Random Effects GLS. Country Dyad Level. Dependent Variable: VC Propensity

	all		foreign–domestic	
	(1)	(2)	(3)	(4)
Path dependencies				
VC prop$_{i\rightarrow j}^{t-1}$	0.300*	0.299*	0.628***	0.628***
	(0.122)	(0.122)	(0.0599)	(0.0598)
Distance				
dist geo$_{i,j}$	−0.00686**	−0.00722**	−0.00164*	−0.00167*
	(0.00255)	(0.00261)	(0.000729)	(0.000726)
dist cult$_{i,j}$	−0.288**	−0.318**	−0.0717*	−0.0747*
	(0.0958)	(0.0993)	(0.0300)	(0.0303)
same legal$_{i,j}$	0.0123*	0.0130**	0.00517**	0.00523**
	(0.00480)	(0.00481)	(0.00188)	(0.00189)
same lang$_{i,j}$	0.0127	0.0131	0.00498	0.00503
	(0.00765)	(0.00766)	(0.00282)	(0.00280)
Trust & Relationship				
trust$_{j}$		0.0172***		0.00173
		(0.00002)		(0.00187)
trade$_{i\rightarrow j}^{t-1}$	0.154	0.148	0.0230	0.0223
	(0.191)	(0.185)	(0.0305)	(0.0299)
Institutions				
cpi$_{j}^{t}$	0.0177	0.0108	0.00947	0.00878
	(0.0364)	(0.0371)	(0.0159)	(0.0163)
inst. stab$_{j}^{t}$	−0.00250	−0.00371*	−0.000779	−0.000900
	(0.00157)	(0.00147)	(0.000842)	(0.000837)
Δcpi_{j-i}^{t}	−0.0191	−0.0217	−0.00303	−0.00330
	(0.0272)	(0.0274)	(0.0103)	(0.0102)
Controls				
gdp$_{j}^{t-1}$	0.157**	0.160***	0.0580***	0.0583***
	(0.0480)	(0.0482)	(0.0161)	(0.0159)
gdp cap$_{j}^{t-1}$	0.146**	0.139**	0.0517*	0.0510*
	(0.0537)	(0.0527)	(0.0244)	(0.0242)
gdp growth$_{j}^{t-1}$	0.0420*	0.0383*	0.0132	0.0128
	(0.0184)	(0.0174)	(0.00983)	(0.00964)
capitalization$_{j}^{t}$	0.0391	0.0454	0.00199	0.00262
	(0.0303)	(0.0301)	(0.00819)	(0.00838)
Δgdp_{j-i}^{t-1}	−0.00700	−0.00847	−0.00135	−0.00150
	(0.00863)	(0.00854)	(0.00346)	(0.00341)
$\Delta gdp\ cap_{j-i}^{t-1}$	−0.126**	−0.127**	−0.0454*	−0.0455*
	(0.0465)	(0.0467)	(0.0222)	(0.0222)
$\Delta gdp\ growth_{j-i}^{t-1}$	−0.0282*	−0.0289*	−0.00800	−0.00808
	(0.0136)	(0.0137)	(0.00608)	(0.00611)
$\Delta capitalization_{j-i}^{t}$	0.0639*	0.0571*	0.0139**	0.0132**
	(0.0286)	(0.0286)	(0.00495)	(0.00501)
$\lambda_{i,j}^{t}$ (imr)	0.00457	0.00591*	0.00185*	0.00198*
	(0.00281)	(0.00272)	(0.000819)	(0.000810)
year dummies	*yes*	*yes*	*yes*	*yes*
N	20,053	20,053	20,053	20,053
R^2	0.1278	0.1281	0.4232	0.4232

Subscript i indicates the source country, j the destination country
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

cross-border VC inflows. However, consistent with 5.c, institutional trust loses its significance when only looking for deals syndicated domestic VCs.[7]

As discussed earlier, we expect the rationales of cross-border venture capital investments to substantially differ when targeting an emerging destination country. Therefore, the next set of regressions, reported in table D.6 contrasts dyadic VC flows with developed (Models 1-4) or emerging destination countries (Models 5-8).

The first striking insight is that both samples differ substantially in terms of coefficient magnitude, direction, significance, and overall model fit. The results for the sub-sample of developed destination countries shows properties similar to the ones reported in table D.12. Again, with a significant $VC\ prop_{i \to j}^{t-1}$, investment activities show path dependencies, and geographical as well as cultural distance have a negative impact on cross-border VC investment activities, lending support to hypothesis 4.a. A negative and significant indicates venture capital to flow from countries with higher growth to those with lower growth, which on first glance appears counter-intuitive. In this sub-sample, the negative effects of corruption on VC activity are particularly strong. When we introduce our measure for relational trust ($VCsynd_{i \to j}^{t}$) in Model 2, representing the share of foreign-domestic syndications in the whole cross-border investment activity, we observe a positive and significant effect. While adding this variable leaves most other coefficients and their corresponding p-values unchanged, it draws a substantial part of the significance of geographical and cultural distance, lending again support to hypothesis 5.a. When investing in developed economies, syndication with domestic partners, which can be interpreted as a result of relational trust, indeed seems to be common practice in mitigating the effects of high geographical, cultural, and institutional distance, a finding that supports hypothesis 5.a. This also holds true when testing for the effect of relational and institutional trust together in Model 4. Surprisingly, institutional trust appears to have no significant effect when only considering investments in developed economies. In line with hypothesis 5.b, our findings suggest that institutional trust is *ex-ante* sufficiently established for developed economies to estimate the viability of investing in a developed jurisdiction.

For the sub-sample of emerging destination countries, the picture changes substantially. The R^2 drops to single-digit values, and most coefficients com-

[7] We additionally ran an unreported (but available on request) model on the whole sample (foreign-only as well as foreign-domestic investments), where we introduced an interaction term between $trust_j$ and $VC\ synd_{i \to j}^{t}$, which turns out to be negative and significant on a 5% level. We interpret this result as further evidence for the suggested mitigating effect of teaming up with a local VC on institutional trust.

Table D.6: Regression table – Random Effects GLS. Country Dyad Level. Dependent Variable: VC Propensity

	(1) developed	(2) emerging	(3) developed	(4) emerging	(5) developed	(6) emerging
		Path dependencies				
VC prop$_{i\to j}^{t-1}$	0.463***	0.162	0.456***	0.149	0.463***	0.162
	(0.0914)	(0.154)	(0.0894)	(0.140)	(0.0914)	(0.154)
			Distance			
dist geo$_{i,j}$	−0.00843**	−0.00621	−0.00554*	−0.00525	−0.00846**	−0.00621
	(0.00278)	(0.00478)	(0.00263)	(0.00474)	(0.00287)	(0.00490)
dist cult$_{i,j}$	−0.360**	0.0681	−0.317*	0.157	−0.361*	0.0684
	(0.136)	(0.122)	(0.138)	(0.147)	(0.145)	(0.141)
same legal$_{i,j}$	0.0146*	0.00149	0.0143*	0.000377	0.0147*	0.00148
	(0.00651)	(0.00770)	(0.00641)	(0.00713)	(0.00659)	(0.00757)
same lang$_{i,j}$	0.0151	−0.00142	0.0118	−0.0103	0.0151	−0.00142
	(0.00781)	(0.00799)	(0.00788)	(0.0104)	(0.00782)	(0.00788)
			Trust & Relationship			
trust$_j$					0.00134	0.00180***
					(0.0113)	(0.0002)
VC synd$_{i\to j}^{t}$			0.0753***	0.351		
			(0.0126)	(0.186)		
trade$_{i\to j}^{t-1}$	0.199	0.230	−0.0174	0.212	0.199	0.230
	(0.366)	(0.221)	(0.357)	(0.207)	(0.366)	(0.221)
$\Delta trust_{j-i}$	0.0103*	0.0239*	0.0117*	0.0201*	0.00970	0.0239
	(0.00482)	(0.0106)	(0.00493)	(0.00893)	(0.00709)	(0.0148)
			Institutions			
cpi$_j^t$	0.0497	−0.124	0.0105	−0.177	0.0484	−0.124
	(0.0264)	(0.101)	(0.0298)	(0.121)	(0.0277)	(0.103)
inst. stab$_j^t$	−0.0103	0.00202	−0.00532	0.0111	−0.0104	0.00204
	(0.00555)	(0.00211)	(0.00519)	(0.00566)	(0.00546)	(0.00287)
Δcpi_{j-i}^t	−0.0172	−0.00390	−0.00535	0.00886	−0.0168	−0.00392
	(0.0188)	(0.0448)	(0.0195)	(0.0478)	(0.0190)	(0.0445)
			Controls			
gdp$_j^{t-1}$	0.149**	0.161*	0.0991*	0.0604	0.150**	0.161*
	(0.0455)	(0.0783)	(0.0467)	(0.105)	(0.0473)	(0.0741)
gdp cap$_j^{t-1}$	0.105*	0.298	0.107*	0.234	0.104*	0.299
	(0.0477)	(0.197)	(0.0473)	(0.165)	(0.0469)	(0.209)
gdp growth$_j^{t-1}$	0.0464***	0.0438	0.0507***	0.0461	0.0464***	0.0438
	(0.0138)	(0.0360)	(0.0137)	(0.0357)	(0.0138)	(0.0373)
capitaliation$_j^t$	0.120	0.153*	0.108	0.176*	0.122	0.153*
	(0.0817)	(0.0643)	(0.0809)	(0.0714)	(0.0877)	(0.0614)
stocks$_j^t$	−0.107	−0.142	−0.123	−0.148	−0.109	−0.142
	(0.0781)	(0.0802)	(0.0792)	(0.0812)	(0.0834)	(0.0747)
Δgdp_{j-i}^{t-1}	−0.0214	−0.00143	0.00233	0.0245	−0.0216	−0.00140
	(0.0189)	(0.0102)	(0.0197)	(0.0223)	(0.0197)	(0.0106)
$\Delta gdp\ cap_{j-i}^{t-1}$	−0.101*	−0.0646	−0.102*	−0.0559	−0.101*	−0.0646
	(0.0467)	(0.0917)	(0.0462)	(0.0843)	(0.0463)	(0.0927)
$\Delta gdp\ growth_{j-i}^{t-1}$	−0.0442***	−0.0268	−0.0463***	−0.0281	−0.0441***	−0.0268
	(0.0113)	(0.0296)	(0.0112)	(0.0290)	(0.0113)	(0.0303)
$\Delta capitalization_{j-i}^t$	−0.156	−0.101*	−0.148	−0.0986*	−0.157	−0.100*
	(0.0937)	(0.0428)	(0.0929)	(0.0410)	(0.0958)	(0.0411)
$\Delta stocks_{j-i}^t$	0.134	0.0944	0.134	0.105	0.134	0.0943
	(0.0818)	(0.0525)	(0.0817)	(0.0553)	(0.0834)	(0.0494)
λ (imr)	0.0109*	−0.00134	0.0106*	−0.00325	0.0110*	−0.00135
	(0.00427)	(0.00238)	(0.00427)	(0.00285)	(0.00452)	(0.00284)
year dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
N	11080	8973	11080	8973	11080	8973
R^2	0.2830	0.0399	0.2893	0.0551	0.2830	0.0399

Subscript i indicates the source country, j the destination country
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

pletely lose their significance. Neither geographical and cultural distance nor commonly used macro variables such as GDP growth or corruption in the destination country seem to have any explanatory power at all, with destination country market capitalization as the only exception. In Model 6, we also introduce relational trust ($VCsynd^{t}_{i \to j}$), which was highly significant in the sub-sample of developed economies. As expected in hypothesis 5.4, in the context of emerging economies, it again loses its explanatory power. Finally, Model 7 includes the measure for institutional trust in the destination country, which, in contrast to the developed economies sub-sample, appears to have a positive coefficient significant at the one-percent level. When jointly testing for the effects of institutional and relational trust in Model 8, the results remain mostly unchanged. However, in this model we find a positive impact of institutional stability, at least at the 10% level.

These results indicate that the utilization of relational trust via the syndication with domestic VCs helps to overcome market entry barriers and transaction costs associated with cross-border investments in a geographical, cultural, or institutional distant country. This finding is, at first glance, in line with recent research on cross-border VC investments (e.g. Dai et al., 2012; Dai and Nahata, 2013; Tykvová and Schertler, 2013), but also highlights that its validity is restricted to practices in developed economies. At least on the aggregated macro level, no evidence for such practices can be found when targeting emerging economies. We find weak evidence for hypothesis 5.b, which suggests that institutional trust has an effect on investments in emerging compared with developed economies. Our results highlight the need to further analyze the drivers of venture capital investment in emerging economies. It also suggests that at least a minimum level of institutional trust seems to be a necessary condition to attract foreign venture capital.

The results thus far suggest substantial qualitative differences between stand-alone investments of foreign VCs and the ones including local co-investors. We also find cross-border investments in developed destination countries to be guided by quite different rationales than the ones targeting emerging economies. Recent research (eg. Dai et al., 2012; Dai and Nahata, 2013)suggests foreign VCs underutilize the potential of joint investments with domestic partners, which our results confirm. To further investigate this issue, we raise the question, in an additional model, how experience and other characteristics of the foreign investors, within and between country, influences the decision to include domestic partners. Thus, in table D.7, we present the results of a logit model with cross-border VC deals as unit of analysis. Our dichotomous dependent variable takes the value of one where the cross-border deal also includes a local VC. Hence, we not aim to analyze the amount, but rather the composition of deals targeting developed vis-à-vis emerging economies. We run the models on the whole population (Models 1 - 2) as well as the subpopulation only consisting of deals in developed (Models 3-4) and emerging (Models 5-6) destination countries. In the first set of models (Models 1, 3, and 5) we test only for the effects of different forms of distance, where we take the mean of all involved foreign VCs to construct our variables for geographical ($dist\ geo_{mean(i,j)}$) and cultural distance ($dist\ cult_{mean(i,j)}$). For legal ($legal_{max(i,j)}$) and lingual similarity ($lan_{max(i,j)}$) we maintain the dichotomous nature of the original variable, and let them take the value of one in the event at least one of the foreign VCs is located in a country with the same language or legal system as the destination country. Since our unit of analysis is now the cross-border VC deal, we are able to also test for experience effects in the portfolio company itself ($exp\ target^t_{max(k)}$), its sector ($exp\ sector^t_{max(k)}$) and finally the destination country ($exp\ country^t_{max(k)}$) of the most experienced foreign VCs in a second set of models (Models 2, 4, and 6).

The results for the whole sample (Models 1-2) again indicate with a negative and significant coefficient for emerging destination countries, that VCs indeed appear to be reluctant to create syndicates with partners from emerging economies. In addition, the comparison between developed (Models 3-4) and emerging (Models 5-6) destination countries reveals some interesting differences.

While corruption (cpi^t_j) negatively affects the tendency for foreign VCs to syndicate with a local VC in developed economies, in emerging economies, it appears to be arguably encourage syndication. Institutional trust ($trust^t_j$), however, has a positive impact in the tendency to form foreign-domestic syndicates in emerging economies. Finally, in contrast to deals in developed economies, in emerging economies geographical distance positively, and cultural distance negatively affects the willingness to syndicate. Overall, foreign-domestic syndicates, particularly in emerging economies, seem to help mitigate the effects of geographical distance, but not necessarily cultural difference. However, while foreign VCs are amendable to syndicating with partners from corrupt destination countries, foreign VCs will still require a minimum level of comfort or trust in a country's institutions.

When introducing experience effects (Models 2, 4, and 6) the maximum investment experience of foreign VCs in the same sector as the investee firm ($exp\ sector^t_{max(k)}$) negatively influences the need to integrate domestic investors, indicating cross-border investments to be even more complicated

Table D.7: Regression table – Logit. Deal Level. Dependent Variable: Domestic participation in cross-border VC deals

	all		developed DC		emerging DC	
	(1)	(2)	(3)	(4)	(5)	(6)
			Destination Country			
gdp_j^t	3.710***	3.184***	2.736***	2.232***	3.584**	3.338*
	(0.502)	(0.480)	(0.700)	(0.645)	(1.344)	(1.433)
gdp $growth_j^t$	-0.0396*	-0.0268	-0.0643*	-0.0698*	-0.103**	-0.0984**
	(0.0166)	(0.0166)	(0.0281)	(0.0279)	(0.0380)	(0.0375)
$capitalization_j^t$	0.00250**	0.00205**	0.00566***	0.00470***	-0.00664***	-0.00673***
	(0.000792)	(0.000769)	(0.00110)	(0.00104)	(0.00143)	(0.00145)
			Dyad			
cpi_j^t	-1.801***	-0.923*	-2.826***	-1.369*	1.138	1.332
	(0.375)	(0.378)	(0.602)	(0.582)	(1.142)	(1.196)
$trust_j$	-0.0694	-0.0710	-0.0552	-0.0766	0.486***	0.477***
	(0.0414)	(0.0410)	(0.0684)	(0.0658)	(0.115)	(0.114)
dist $geo_{mean(i,j)}$	0.0812**	0.0787**	0.0429	0.0379	0.418***	0.431***
	(0.0276)	(0.0272)	(0.0297)	(0.0291)	(0.111)	(0.115)
dist $cult_{mean(i,j)}$	-3.707**	-1.308	-3.460*	-0.891	-2.08***	-2.39***
	(1.384)	(1.422)	(1.478)	(1.526)	(5.539)	(5.660)
same $legal_{max(i,j)}$	0.273**	0.270**	0.327**	0.306**	0.633**	0.587*
	(0.0985)	(0.0988)	(0.118)	(0.116)	(0.230)	(0.232)
same $lang_{max(i,j)}$	-0.206*	-0.175	-0.310**	-0.269*	-0.224	-0.206
	(0.0991)	(0.0994)	(0.116)	(0.114)	(0.244)	(0.246)
$emerging_j$	-0.783***	-0.635***				
	(0.146)	(0.143)				
			Acquiring foreign VCs			
exp $sector_{max(k)}^t$		-0.00533***		-0.00704***		-0.000729
		(0.000870)		(0.00103)		(0.00187)
exp $country_{max(k)}^t$		0.0281***		0.0337***		-0.00661
		(0.00321)		(0.00396)		(0.0124)
exp $target_{max(k)}^t$		0.525***		0.542***		0.451**
		(0.0586)		(0.0652)		(0.151)
year dummies	yes	yes	yes	yes	yes	yes
N	7251	7251	6056	6056	1195	1195
Pseudo R^2	0.1029	0.1271	0.0395	0.0711	0.1131	0.1186
log Pseudoliklihood	-4375.305	-4257.428	-3704.637	-3582.7357	-618.504	-614.615

Subscript i indicates the source country, j the destination country, and k the acquiring VC
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

when carried out in an unfamiliar sector. Put differently, foreign VCs are less likely to seek local syndicated expertise if they feel they have sufficient sector experience. The experience in the destination country ($exp\ country^{t}_{max(k)}$), in turn, has a positive effect, indicating that domestic partners are found after all in existing networks in the destination country. Both, however, are only true for the sub sample of developed economies. A possible explanation is that VCs indeed struggle to identify, generally avoid, or prematurely terminate relationships with domestic partners in emerging economies due to friction, prejudices, or dissatisfaction.

3.5 Robustness tests

To ensure that our results are not solely driven by our choice of how to construct the dependent variable, we also ran a set of alternative models. In the reported models, we not only construct the dependent variable in a way where every deal adds one count to all participating source countries, but we also run models where deals either count once per investor for every destination country, or only for the destination country with the largest number of investors. We also replace the number of deals by their value in US dollars. Zephyr unfortunately has no information on the amount invested by individual investors, so we have to assume that all investors participate in the deal with equal investments.[8]Furthermore, we run the same variable set up in a zero-inflated negative binomial model with the VC deal count between a country dyad as a dependent variable.[9]Overall, these measures lead to quite comparable, but less pronounced, results and a lower but acceptable significance and goodness-of-fit of the models. We also tried alternative measures for our institutional trust variable, such as the indices for the quality of law, the government, investor protection, and accountability provided by the World Bank. While less pronounced, these results point in the same direction.

[8]Unfortunately, In Zephyr the deal value is missing in about 30 percent of the cases, hence decreases our number of available observations

[9]The test for over-dispersion (likelihood ratio test of α=0) confirms our choice of a negative binomial over a possion model. To evaluate the benefits of the applied two-stage zero inflation procedure, we carry out the likelihood ratio test for model selection suggested by Vuong (1989), where the results speak in favor of our choice.

4 Conclusion

In this paper, we analyze the effects of geographical, cultural, and institutional proximity as well as institutional and relational trust on cross-border VC flows between country dyads. We contrast cross-border investments made by only foreign VCs with investments made by both foreign and local VCs in syndicate. We further analyze cross-border venture capital investment between developed and emerging economies, as many emerging economies have been actively supporting their own venture capital markets pursuant to the perceived success of VC contribution to innovation in more developed jurisdictions (Bruton et al., 2008, 2005). These same economies are seeking not only to attract foreign funds but more specifically foreign expertise as it is thought that not only would local entrepreneurs benefit from specialist VC skills, but also that local VCs would benefit from the transfer of knowledge from the more sophisticated foreign VCs. However, underdeveloped investor and property protection, high cultural distance, diverging business ethics and practices, and the perception of corruption in certain jurisdictions are obstacles to the development of these markets. An example of a jurisdiction that has faced such challenge is China, and it is this jurisdiction that we have looked to for the motivation of this research. Despite the institutional obstacles, China has been able to not only build a venture capital market from scratch since 1984 (Xiao, 2002) but has been able to develop it to the success it is today, and this has been attributed to guanxi, or network-based strategies, utilized by market participants (Peng, 2003; Pukthuanthong and Walker, 2007; Su et al., 2007). By taking into account more jurisdictions, we believe our research provides a more thorough understanding of the balance between institutional factors and network effects from a pattern of international alliances and syndicates in the venture capital industry. In line with prior research, we find evidence that foreign venture capital flow into developed economies is facilitated by the building of relational trust among foreign VCs investing as a syndicate comprising local VCs. However, we find the driving forces of cross-border VC investment activities in emerging economies to be substantially different and widely unexplained by traditional mechanisms used to analyze venture capital flows in the context of developed economies. Consistent with Rousseau et al. (1998), our results suggest institutional trust to be a necessary precondition for foreign VC inflow as well as the formation of foreign-domestic syndicates. Institutional trust thus provides the foundation for building up a critical mass of initial trust to enter a relationship involving proximity.

Our findings highlight not only the need for further analysis of the driving forces of cross-border venture capital flows, but more specifically the need for analysis to explicitly consider investments in emerging economies. We believe our paper sheds light on a yet under-explored facet driving cross-border venture capital investments and thereby provides guidance for academics on how to integrate more socio-economic determinants in macroeconomic venture capital investment analyses. Future research for example could shed even more light by looking at the effect of changes in the perceptions of trust or changes in political stability (instability) on venture capital fund flows. An analysis of the effect of having a VC partner from the host country on profitability and other performance metrics could also further extend this research. For policy makers, we believe our findings may shed light on the determinants of not only venture capital inflow but also the inflow of VC expertise. As our findings suggest, sophisticated VCs are not necessarily transferring valuable knowledge, such as sector expertise, to local syndicate members but are more likely to extract such knowledge. To tap foreign sources of knowledge and capital, more needs to be done by policy makers in emerging economies to instill institutional trust which appears to be a necessary precondition for foreign venture capital inflow. For example, in China, policies to attract foreign venture capital emphasize strengthening the legal environment. Guanxi can only get you so far.

References

Ahlstrom, D. and Bruton, G. D. (2006). Venture capital in emerging economies: Networks and institutional change. *Entrepreneurship Theory and Practice*, 30(2):299–320.

Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Eeconomic Studies*, 29(3):155–173.

Avnimelech, G., Kenney, M., and Teubal, M. (2006). Creating venture capital industries that co-evolve with high tech: Insights from an extended industry life cycle perspective of the Israeli experience. *Research Policy*, 35(10):1477–1498.

Baygan, G. and Freudenberg, M. (2000). The internationalisation of centure capital activity in oecd countries: implications for measurement and policy. STI Working Paper Series.

Beck, T., Feyen, E., Ize, A., and Moizeszowicz, F. (2008). Benchmarking financial development. *World Bank Policy Research Working Paper 4638*.

Bergemann, D. and Hege, U. (1998). Venture capital financing, moral hazard, and learning. *Journal of Banking & Finance*, 22(6-8):703–735.

Berger, A. and Frame, W. (2007). Small business credit scoring and credit availability. *Journal of Small Business Management*, 45(1):5–22.

Berger, A. and Udell, G. (2002). Small business credit availability and relationship lending: The importance of bank organisational structure. *The Economic Journal*, 112(477):F32–F53.

Beugelsdijk, S. (2006). A note on the theory and measurement of trust in explaining differences in economic growth. *Cambridge Journal of Economics*, 30(3):371–387.

Black, B. and Gilson, R. (1998). Venture capital and the structure of capital markets: banks versus stock markets. *Journal of Financial Economics*, 47(3):243–277.

Blau, P. M. (1964). *Exchange and Power in Social Life*. Transaction Publishers.

Boschma, R. and Frenken, K. (2010). The spatial evolution of innovation networks. a proximity perspective. In Boschma, R. A. and Martin, R. L., editors, *Handbook on Evolutionary Economic Geography*, pages 120–135.

Boschma, R. A. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, 39(1):61–74.

Bottazzi, L., Da Rin, M., and Hellmann, T. F. (2011). The importance of trust for investment: Evidence from venture capital. NBER Working Paper 16923.

Bruton, G., Ahlstrom, D., and Yeh, K. S. (2004). Understanding venture capital in east Asia: the impact of institutions on the industry today and tomorrow. *Journal of World Business*, 39(1):72–88.

Bruton, G. D. and Ahlstrom, D. (2003). An institutional view of china's venture capital industry: Explaining the differences between china and the west. *Journal of Business Venturing*, 18(2):233–259.

Bruton, G. D., Ahlstrom, D., and Obloj, K. (2008). Entrepreneurship in emerging economies: Where are we today and where should the research go in the future. *Entrepreneurship theory and practice*, 32(1):1–14.

Bruton, G. D., Fried, V. H., and Manigart, S. (2005). Institutional influences on the worldwide expansion of venture capital. *Entrepreneurship Theory and Practice*, 29(6):737–760.

Bygrave, W. D. and Timmons, J. A. (1992). *Venture capital at the crossroads*. Harvard Business Press.

Casamatta, C. and Haritchabalet, C. (2007). Experience, screening and syndication in venture capital investments. *Journal of Financial Intermediation*, 16(3):368–398.

CEPII (1990–2011). Cepii database.

Chemmanur, T. J., Hull, T., and Krishnan, K. (2011). Do local and international venture capitalists play well together? a study of international venture capital investments. AFA 2012 Chicago Meetings Paper.

Coval, J. D. and Moskowitz, T. J. (1999). Home bias at home: Local equity preference in domestic portfolios. *The Journal of Finance*, 54(6):2045–2073.

Coval, J. D. and Moskowitz, T. J. (2001). The geography of investment: Informed trading and asset prices. *Journal of Political Economy*, 109(4):811–841.

Cumming, D. J. (2003). The structure, governance and performance of uk venture capital trusts. *Journal of Corporate Law Studies*, 3(2):401–427.

Cumming, D. J. (2006). Adverse selection and capital structure: evidence from venture capital. *Entrepreneurship Theory and Practice*, 30(2):155–183.

Cumming, D. J. (2010a). Review essay: Public policy and the creation of active venture capital markets and some comments on'boulevard of broken dreams: Why public efforts to boost entrepreneurship and venture capital have failed–and what to do about it,'by josh lerner. *Venture Capital: An International Journal of Entrepreneurial Finance, Forthcoming*.

Cumming, D. J. (2010b). *Venture Capital: Investment Strategies, Structures, and Policies*, volume 9. Wiley.

Cumming, D. J. (2011). Review essay: Public policy and the creation of active venture capital markets. *Venture Capital: An International Journal of Entrepreneurial Finance*, 13(1):75–94.

Cumming, D. J. and Dai, N. (2010). Local bias in venture capital investments. *Journal of Empirical Finance*, 17(3):362–380.

Cumming, D. J. and Johan, S. A. (2006a). Is it the law or the lawyers? investment covenants around the world*. *European Financial Management*, 12(4):535–574.

Cumming, D. J. and Johan, S. A. (2006b). Provincial preferences in private equity. *Financial Markets and Portfolio Management*, 20(4):369–398.

Cumming, D. J. and Johan, S. A. (2007). Advice and monitoring in venture finance. *Financial Markets and Portfolio Management*, 21(1):3–43.

Cumming, D. J. and Johan, S. A. (2013). *Venture capital and private equity contracting: An international perspective*. Academic Press.

Dai, N., Jo, H., and Kassicieh, S. (2012). Cross-border venture capital investments in Asia: selection and exit performance. *Journal of Business Venturing*, 27:666–684.

Dai, N. and Nahata, R. (2013). Cultural differences and cross-border venture capital syndication. working paper.

Davila, A., Foster, G., and Gupta, M. (2003). Venture capital financing and the growth of startup firms. *Journal of Business Venturing*, 18(6):689–708.

Davis, J. H. and Ruhe, J. A. (2003). Perceptions of country corruption: Antecedents and outcomes. *Journal of Business Ethics*, 43(4):275–288.

Dosi, G. (1982). Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. *Research policy*, 11(3):147–162.

Dosi, G. (1988). Sources, procedures, and microeconomic effects of innovation. *Journal of economic literature*, pages 1120–1171.

Dovey, K. (2009). The role of trust in innovation. *The Learning Organization*, 16(4):311–325.

Duffner, S., Schmid, M. M., and Zimmermann, H. (2009). Trust and success in venture capital financing – an empirical analysis with german survey data. *KYKLOS*, 62(1):15–43.

Engel, D. and Keilbach, M. (2007). Firm-level implications of early stage venture capital investment—an empirical investigation. *Journal of Empirical Finance*, 14(2):150–167.

Eurobarometer (1990–2011). Eurostat eurobarometer.

Farmer, R. E. and Winter, R. A. (1986). The role of options in the resolution of agency problems: a comment. *The Journal of Finance*, 41(5):1157–1170.

Feenstra, R., Lipsey, R., Deng, H., Ma, A., and Mo, H. (2005). World trade flows: 1962-2000. Technical report, National Bureau of Economic Research.

Fiet, J. O. (1995a). Reliance upon informants in the venture capital industry. *Journal of Business Venturing*, 10(3):195–223.

Fiet, J. O. (1995b). Risk avoidance strategies in venture capital markets. *Journal of Management Studies*, 32(4):551–574.

Fiet, J. O. (1996). The informational basis of entrepreneurial discovery. *Small Business Economics*, 8(6):419–430.

Foray, D. and Lundvall, B. (1996). The knowledge-based economy: from the economics of knowledge to the learning economy. *Employment and Growth in the Knowledge-based Economy*, pages 11–32.

Freel, M. (2007). Are small innovators credit rationed? *Small Business Economics*, 28(1):23–35.

French, K. and Poterba, J. (1991). Investor diversification and international equity markets. *American Economic Review*, 81:222–226.

Giannetti, M. and Yafeh, Y. (2012). Do cultural differences between contracting parties matter? evidence from syndicated bank loans. *Management Science*, 58(2):365–383.

Gompers, P. A., Kovner, A., Lerner, J., and Scharfstein, D. (2008). Venture capital investment cycles: The impact of public markets. *Journal of Financial Economics*, 87(1):1–23.

Guiso, L., Sapienza, P., and Zingales, L. (2008). Trusting the stock market. *The Journal of Finance*, 63(6):2557–2600.

Guiso, L., Sapienza, P., and Zingales, L. (2009). Cultural biases in economic exchange? *Quarterly Journal of Economics*, 124(3):1095–1131.

Guler, I. and Guillén, M. F. (2005). Knowledge, institutions, and foreign entry: The internationalization of us venture capital firms. Working Paper Draft.

Guler, I. and Guillén, M. F. (2010). Institutions and the internationalization of us venture capital firms. *Journal of International Business Studies*, 41(2):185–205.

Hall, B. H. (2010). The financing of innovative firms. *Review of Economics and Institutions*, 1(1):1–30.

Hall, B. H. and Lerner, J. (2009). The financing of r&d and innovation. NBER Working Paper 15325.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, pages 153–161.

Hofstede, G. and Bond, M. H. (1984). Hofstede's culture dimensions. *Journal of Cross-Cultural Psychology*, 15(4):417.

Hofstede, G., Hofstede, G. J., and Minkov, M. (2010). *Cultures and organizations: Software of the mind*. McGraw-Hill London.

Hsu, D. H. (2004). What do entrepreneurs pay for venture capital affiliation? *The Journal of Finance*, 59(4):1805–1844.

Huntington, S. and Fukuyama, F. (2006). *Political order in changing societies*. Yale University Press.

Jääskeläinen, M., Maula, M., and Seppä, T. (2006). Allocation of attention to portfolio companies and the performance of venture capital firms. *Entrepreneurship Theory and Practice*, 30(2):185–206.

Johan, S., Knill, A., and Mauck, N. (2013). Determinants of sovereign wealth fund investment in private equity. *Journal of International Business Studies*, 44:155–172.

Johan, S. A. and Najar, D. (2010). The role of corruption, culture, and law in investment fund manager fees. *Journal of business ethics*, 95(2):147–172.

Kaufmann, D., Kraay, A., and Mastruzzi, M. (2010). The worldwide governance indicators: methodology and analytical issues. *World Bank policy research working paper*, (5430).

Kendall, J. and Aizenman, J. a. (2012). The internationalization of venture capital. *Journal of Economic Studies*, 39(5).

Knack, S. and Keefer, P. (1997). Does social capital have an economic payoff? a cross-country investigation. *The Quarterly Journal of Economics*, 112(4):1251.

Kogut, B. and Singh, H. (1988). The effect of national culture on the choice of entry mode. *Journal of international business studies*, pages 411–432.

Kortum, S. and Lerner, J. (1998). Does venture capital spur innovation? NBER Working Paper 6846: Available at: http://www.nber.org/papers/w6846.

Kortum, S. and Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *RAND Journal of Economics*, pages 674–692.

Krugman, P. (1980). Scale economies, product differentiation, and the pattern of trade. *The American Economic Review*, 70(5):950–959.

La Porta, R., Lopez-de Silane, F., Shleifer, A., and Vishny, R. W. (1998). Law and finance. *Journal of Political Economy*, 106(6):1133–1155.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., and Vishny, R. (2000). Investor protection and corporate governance. *Journal of financial economics*, 58(1):3–27.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., and Vishny, R. W. (1997). Legal determinants of external finance. *The journal of finance*, 52(3):1131–1150.

Leff, N. H. (1964). Economic development through bureaucratic corruption. *American Behavioral Scientist*, 8(3):8–14.

Levy, D. (2007). Price adjustment under the table: Evidence on efficiency-enhancing corruption. *European Journal of Political Economy*, 23(2):423–447.

Lu, H., Tan, Y., and Huang, H. (2013). Why do venture capital firms exist: An institution-based rent-seeking perspective and chinese evidence. *Asia Pacific Journal of Management*, 30(3):921–936.

Mäkelä, M. M. and Maula, M. (2008). Attracting cross-border venture capital: the role of a local investor. *Entrepreneurship and Regional Development*, 20(3):237–257.

Manigart, S., Lockett, A., Meuleman, M., Wright, M., Landstrm, H., Bruining, H., Desbrieres, P., and Hommel, U. (2002). Why do European venture capital companies syndicate. *Ghent University and Ghent Management School Working Paper*.

Mayer, T. and Zignago, S. (2011). Notes on cepii's distances measures: The geodist database. Working Papers 2011-25, CEPII.

McAllister, D. J. (1995). Affect-and cognition-based trust as foundations for interpersonal cooperation in organizations. *Academy of Management Journal*, 38(1):24–59.

Megginson, W. L. (2004). Toward a global model of venture capital? *Journal of Applied Corporate Finance*, 16(1):89–107.

Melitz, J. and Toubal, F. (2012). Native language, spoken language, translation and trade. Working Papers 2012-17, CEPII.

Nahata, R. (2008). Venture capital reputation and investment performance. *Journal of Financial Economics*, 90(2):127–151.

Nahata, R., Hazarika, S., and Tandon, K. (2013). Success in global venture capital investing: do institutional and cultural differences matter? *Journal of Financial and Quantitative Analysis, Forthcoming*.

Nielsen, R. P. (2003). Corruption networks and implications for ethical corruption reform. *Journal of Business ethics*, 42(2):125–149.

Nooteboom, B. (2006). Trust and innovation. *Essay written for the Dutch Ministry of Economic Affairs*.

North, D. (1990). *Institutions, institutional change and economic performance*. Cambridge University Press.

Parwada, J. T. (2008). The genesis of home bias? the location and portfolio choices of investment company start-ups. *Journal of Financial and Quantitative Analysis*, 43(01):245–266.

Peng, M. W. (2001). How entrepreneurs create wealth in transition economies. *The Academy of Management Executive*, 15(1):95–108.

Peng, M. W. (2003). Institutional transitions and strategic choices. *Academy of management review*, 28(2):275–296.

Polanyi, M. (1966). *Personal knowledge: Towards a post-critical philosophy*. Chicago: University of Chicago Press.

Pöyhönen, P. (1963). A tentative model for the volume of trade between countries. *Weltwirtschaftliches Archiv*, 90(1):93–100.

Pukthuanthong, K. and Walker, T. (2007). Venture capital in china: a culture shock for western investors. *Management Decision*, 45(4):708–731.

Romain, A. and Van Pottelsberghe, B. (2004a). The determinants of venture capital: a panel data analysis of 16 oecd countries. *Research Institute in Management Science Working Paper*.

Romain, A. and Van Pottelsberghe, B. (2004b). The determinants of venture capital: Additional evidence. *Discussion Paper Series 1: Economic Studies*.

Rousseau, D. M., Sitkin, S. B., Burt, R. S., and Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *Academy of Management Review*, 23(3):393–404.

Sahlman, W. (1990). The structure and governance of venture-capital organizations. *Journal of Financial Economics*, 27(2):473–521.

Samila, S. and Sorenson, O. (2010). Venture capital as a catalyst to commercialization. *Research Policy*, 39:1348–1360.

Samila, S. and Sorenson, O. (2011). Venture capital, entrepreneurship, and economic growth. *The Review of Economics and Statistics*, 93(1):338–349.

Sapienza, H. J. (1992). When do venture capitalists add value? *Journal of Business Venturing*, 7(1):9–27.

Sapienza, H. J., Manigart, S., and Vermeir, W. (1996). Venture capitalist governance and value added in four countries. *Journal of Business Venturing*, 11(6):439–469.

Schertler, A. and Tykvová, T. (2009). Venture capital and internationalization. *ZEW Discussion Papers*.

Schertler, A. and Tykvová, T. (2010). What lures cross-border venture capital inflows? *ZEW Discussion Papers*.

Shepherd, D. A. and Zacharakis, A. (2001). The venture capitalist-entrepreneur relationship: control, trust and confidence in co-operative behaviour. *Venture Capital: An International Journal of Entrepreneurial Finance*, 3(2):129–149.

Sorenson, O. and Stuart, T. E. (2001). Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology*, 106(6):1546–88.

Su, C., Mitchell, R. K., and Sirgy, M. J. (2007). Enabling guanxi management in china: A hierarchical stakeholder model of effective guanxi. *Journal of Business Ethics*, 71(3):301–319.

Survey, W. V. (2009). World value survey 2005 official data file v.20090901.

Tan, J. and Tan, D. (2005). Environment-strategy co-evolution and co-alignment: A staged model of chinese soes under transition. *Strategic Management Journal*, 26(2):141.

Tinbergen, J. (1962). An analysis of world trade flows. *Shaping the world economy*.

Tykvová, T. and Schertler, A. (2008). Syndication to overcome transaction costs of cross-border investments? evidence from a worldwide private equity deals? dataset. Technical report, Working paper.

Tykvová, T. and Schertler, A. (2013). Geographical and institutional distances in venture capital deals: How syndication and experience drive internationalization patterns. ZEW Discussion Paper No. 11-022.

Von Hippel, E. (1994). Sticky information and the locus of problem solving: Implications for innovation. *Management Science*, 40(4):429–439.

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica: Journal of the Econometric Society*, pages 307–333.

Wilhelm, P. G. (2002). International validation of the corruption perceptions index: Implications for business ethics and entrepreneurship education. *Journal of Business Ethics*, 35(3):177–189.

Wright, M., Pruthi, S., and Lockett, A. (2005). International venture capital research: From cross-country comparisons to crossing borders. *International Journal of Management Reviews*, 7(3):135–165.

Xiao, W. (2002). The new economy and venture capital in china. *Perspectives*, 3(6):30.

Zephyr (2012). Zephyr m&a database.

Appendix

Table D.8: Venture Capital Flows on Country Level

	AT	BE	CH	DE	DK	ES	FI	FR	GB	GR	IE	IT	JP	NL	NO	PT	SE	US
Domestic investments																		
Volume	400	669	748	6,014	799	1,420	697	0	11,823	15	582	690	352	1,205	292	43	1,498	126,961
Number	80	155	136	1145	166	309.0	167	0	2,433	4.00	201	86	151	224	57	12	362	11,794
Gross cross-border inflow (from all sample countries)																		
Volume	105	363	647	1,444	344	232	241	0	3,593	0	356	226	18	625	166	16	556	10,020
Number	26	98	175	427	105	47	81	0	763	0	137	34	14	117	33	8	182	2,402
Gross cross-border outflow (to all sample countries)																		
Volume	22	576	1,905	2,198	465	104	170	1,270	4,878	0	151	143	1,616	870	229	12	538	3,801
Number	9	185	487	552	138	26	62	367	1,152	0	51	54	367	286	91	6	163	653

Note: This table reports the aggregated venture capital investments, in- and outflows in the period between 2000 to 2013 on country level, measured in million EURO and alternatively in the number of investments. For the sake of brevity, only the top quantile of countries in terms of VC activity are reported

Table D.9: Matrix: Venture Capital investments per country/year

year	AT	AU	BE	BG	BR	CA	CH	CN	DE	DK	ES	FI	FR	GB	HK	IE	IL	IN	IT	JP	KR	NL	NO	PL	RU	SE	SG	US	$\sum j$
Outflow from source country																													
2000	6	2	55	0	0	55	58	0	209	29	23	33	199	524	3	32	53	0	27	29	0	101	4	1	0	83	18	1,481	3,025
2001	11	0	58	0	2	107	53	0	245	40	13	28	167	476	4	37	70	1	10	33	0	87	6	2	0	94	33	1,279	2,856
2002	3	2	32	0	2	91	45	0	137	28	16	14	138	335	0	25	53	0	8	29	0	39	11	1	0	42	14	1,062	2,127
2003	5	7	33	0	3	103	29	0	107	35	17	18	105	324	1	19	62	1	5	27	0	28	12	0	0	37	13	1,110	2,101
2004	7	8	28	0	3	106	49	4	113	37	13	25	111	339	8	17	96	1	3	31	0	28	6	0	0	37	14	1,276	2,360
2005	4	12	19	0	1	83	51	14	92	24	22	15	117	274	3	23	75	3	7	32	1	30	15	1	0	34	14	1,101	2,067
2006	2	6	22	0	1	65	63	19	148	20	15	17	133	287	7	13	66	7	9	50	1	28	11	0	1	27	14	1,107	2,139
2007	5	12	30	0	0	82	74	22	177	27	20	11	96	280	7	6	69	4	7	58	3	41	10	2	1	43	4	1,332	2,423
2008	3	10	21	0	0	62	62	38	181	14	50	10	77	242	10	9	64	19	9	44	2	36	9	3	1	34	8	1,067	2,085
2009	5	7	21	0	0	44	66	33	145	16	31	12	148	242	4	24	57	15	12	38	0	37	7	5	5	25	8	972	1,979
2010	4	8	16	0	0	54	56	47	131	24	45	11	132	225	8	20	39	19	15	55	3	29	11	15	8	29	6	995	2,005
2011	3	13	16	0	7	98	68	82	156	24	70	8	165	253	17	30	60	17	17	75	9	44	5	16	23	41	22	1,672	3,011
2012	3	14	17	0	13	144	58	56	161	34	43	27	150	291	15	25	46	54	24	77	5	45	8	0	25	35	23	2,139	3,532
2013	5	10	17	0	13	141	54	63	177	26	80	58	123	237	18	24	55	64	59	81	10	93	5	0	92	28	46	1,946	3,525
Inflow to destination country																													
2000	10	2	27	0	1	29	23	0	150	21	29	35	174	368	2	31	27	4	17	2	0	55	3	3	0	81	1	1,343	2,438
2001	11	2	30	0	2	54	14	2	160	26	17	29	147	288	1	38	50	2	7	0	2	31	4	3	0	84	3	1,184	2,191
2002	3	2	15	0	2	60	16	0	79	21	16	16	112	198	1	29	26	2	4	3	0	10	7	2	0	27	4	981	1,636
2003	5	4	14	0	4	63	8	2	51	26	18	14	79	222	1	18	28	2	2	5	1	8	6	0	0	24	0	1,040	1,645
2004	9	5	9	0	4	70	10	11	49	20	17	20	88	217	1	21	48	3	1	6	1	9	6	1	0	17	1	1,191	1,835
2005	7	6	3	0	1	54	11	29	48	16	18	8	91	200	0	20	61	8	5	14	1	13	7	1	0	14	2	1,017	1,655
2006	7	2	13	0	1	44	13	47	109	9	16	14	114	210	0	9	55	26	8	36	2	12	3	0	0	26	3	993	1,772
2007	7	4	15	0	0	67	18	43	143	12	19	7	73	202	2	6	56	19	7	40	4	24	4	3	1	26	2	1,220	2,024
2008	6	6	10	0	1	40	19	70	162	6	51	7	60	204	0	8	46	20	6	30	2	24	8	3	2	25	3	976	1,795
2009	12	4	9	0	1	26	18	54	116	3	27	6	107	183	1	20	42	33	8	31	4	23	6	5	3	16	1	894	1,653
2010	5	8	8	0	0	38	19	75	110	9	39	12	95	185	2	17	36	25	13	36	3	15	8	17	6	23	5	926	1,735
2011	9	10	8	1	9	88	20	101	138	11	68	10	118	181	1	22	40	26	14	55	8	18	3	15	18	38	13	1,547	2,590
2012	4	12	9	22	25	123	16	72	135	11	44	23	122	219	4	22	37	87	26	48	2	8	6	3	13	33	14	1,931	3,071
2013	6	12	10	58	26	127	18	68	137	14	58	59	76	183	1	20	41	103	57	67	4	31	3	2	75	21	19	1,758	3,054

Note: This table reports the aggregated amount venture capital inflow/outflow to/from the corresponding destination/source countries during the observation period from 2000 to 2013. For the sake of brevity, only the top quantile of countries in terms of VC activity are reported

Table D.10: Variable Description

Variable	Description	Source
	Macro Models	
	Dependent Variables	
$VC^t_{i \to j}$	Number of venture capital deals in destination country j with participating venture capitalists from source country i	Zephyr (2012)
VC $prop^t_{i \to j}$	Venture capital propensity between source country i and destination country j, as in equation **??**	Zephyr (2012)
	Distance	
dist $geo_{i,j}$	Natural logarithm of the distance in kilometers between the source country j and the destination country i, adjusted to population density	CEPII (2011)
dist $cult_{i,j}$	Cultural distance between source country j, as in equation **??**	Own construction from Hofstede et al. (2010)
same $legal_{i,j}$	Dummy variable, indicating the same origin of the legal system in source i and destination country j (categorized in french, german, english, scandinavian)	La Porta et al. (1998)
same $lang_{i,j}$	Dummy, indicating a shared language spoken by at least ten percent of population in source j and destination country i	CEPII (2011)
	Trust & Relationships	
$trust_j$	Percentage of citizens of the destination country i who replied to the question: "Generally speaking, would you say that most people can be trusted?" with "Yes"	World Value Survey
VC $synd^t_{i \to j}$	Share of deals carried out in syndication between foreign venture capitalists from source country i with domestic ones in destination country j to all investments from source country i in destination country j	Zephyr (2012)
$trade^t_{i \to j}$	Trade flow relative to GDP between Source country i and destination country j, normalized, as in equation **??**	OECD STAN database
	Institutions	
cpi^t_j	Corruption Perception Index of destination country j, adjusted to 0-1 scale, where high values indicate low levels of corruption	Transparency International
inst $stab^t_j$	Institutional stability of destination country j, standardized on -2.5 - 2.5 scale, where high values indicate high instability	Kaufmann et al. (2010)
	Controls	
gdp^t_j	GDP of destination country j, constant 2005 USD	Worldbank Development Indicators
gdp $growth^t_j$	GDP growth of destination country j in percentage	Worldbank Development Indicators
$capitalization^t_j$	Ratio of market capitalization of listed companies to GDP in destination country j	Worldbank Development Indicators
$stocks^t_j$	Ratio of stocks traded to GDP in destination country j	Worldbank Development Indicators
	Micro Models	
	Dependent Variables	
VC host	Dummy variable, indicating whether or not the cross-border VC deal also includes a domestic VC	Zephyr (2012)
	Dyad	
dist $geo_{mean(i,j)}$	Mean of geographical distance between destination country and country of residence of the foreign VCs	CEPII (2011)
dist $cult_{mean(i,j)}$	Mean of cultural distance between destination country and country of residence of the foreign VCs	Hofstede et al. (2010)
$legal_{max(i,j)}$	Dummy variable, indicating whether or not at least one of the foreign VCs comes from a country with the same legal tradition	La Porta et al. (1998)
$lang_{max(i,j)}$	Dummy variable, indicating whether or not at least one of the foreign VCs comes from a country with the same language	CEPII (2011)
	Acquiring foreign VCs	
exp $sector^t_{max(k)}$	Maximum of the participating foreign VCs experience in the PC sector	Zephyr (2012)
exp $country^t_{max(k)}$	Maximum of the participating foreign VCs experience in the DC	Zephyr (2012)
exp $target^t_{max(k)}$	Maximum of the participating foreign VCs experience with the same PC	Zephyr (2012)

Overview and definition of variables and data-sources

Table D.11: Matrix: Venture Capital investments between Country Pairs

$i \Rightarrow$ $,j \Downarrow$	AT	AU	BE	BG	BR	CA	CH	CN	DE	DK	ES	FI	FR	GB	HK	IE	IL	IN	IT	JP	KR	NL	NO	PL	RU	SE	SG	US	$\sum j$
AT		0	0	0	0	0	2	0	6	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9
AU	0		0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	59	62
BE	2	0		0	0	0	15	0	21	2	1	1	42	45	0	11	9	0	1	0	0	30	0	0	0	1	5	92	278
BG	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BR	0	0	0	0		0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3	6
CA	0	0	0	0	0		0	0	4	0	0	1	6	16	0	5	2	0	0	0	0	5	0	0	0	2	1	530	572
CH	10	4	8	0	0	13		6	126	13	4	3	20	57	0	13	6	2	7	0	1	11	4	0	0	7	5	378	698
CN	0	0	0	0	0	0	0		0	0	0	0	0	1	3	0	0	0	0	0	2	0	0	0	0	0	6	40	52
DE	43	3	8	0	3	22	56	5		13	5	5	50	100	0	9	40	2	7	0	1	25	2	14	7	7	2	410	839
DK	2	0	0	0	0	4	11	0	16		0	12	7	25	1	1	0	0	0	0	0	3	1	0	0	34	0	99	216
ES	0	0	0	0	7	2	3	0	4	0		0	4	12	0	2	1	1	0	0	0	2	0	0	0	2	0	24	64
FI	2	0	0	0	0	4	1	0	1	8	1		0	3	0	0	0	0	1	0	0	1	1	1	0	26	0	25	75
FR	7	0	40	0	0	18	62	5	67	12	9	5		102	0	10	9	3	2	1	0	23	2	0	2	12	1	219	611
GB	19	3	22	1	2	18	41	9	200	28	56	44	192		1	66	38	4	31	3	0	37	13	1	4	70	8	927	1,838
HK	0	0	0	0	0	4	0	28	1	0	0	0	0	15		0	4	9	0	0	0	0	0	0	0	0	2	42	105
IE	2	0	0	0	0	1	1	1	0	0	1	0	1	43	0		0	0	0	0	0	0	0	0	0	0	0	26	76
IL	0	0	0	0	1	5	0	6	0	0	0	0	6	38	0	3		1	0	0	0	2	0	0	0	0	0	527	589
IN	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0		0	0	0	0	0	0	0	0	0	21	23
IT	2	0	0	0	0	0	0	0	3	0	6	2	14	27	0	0	10	0		0	0	0	0	0	0	0	1	15	80
JP	0	2	2	0	0	2	2	27	2	1	0	0	14	30	1	1	5	1	1		3	1	0	0	0	6	6	231	338
KR	0	0	0	0	0	3	0	1	0	0	0	0	0	1	0	0	0	0	0	0		0	0	0	0	0	0	8	13
NL	10	0	38	80	0	8	16	0	58	15	5	7	30	78	1	6	8	0	5	0	0		3	0	0	8	0	102	478
NO	0	0	0	0	0	0	12	0	2	6	0	0	1	20	0	0	0	0	0	0	0	0		0	0	22	0	27	90
PL	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	1
RU	0	0	0	0	0	0	0	0	9	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0		0	1	35	47
SE	0	1	0	0	1	1	8	2	7	25	2	26	10	16	0	0	2	1	1	0	0	0	28	0	1		0	85	217
SG	0	3	1	0	0	3	3	23	3	5	0	0	10	14	0	5	2	7	0	12	0	1	0	0	0	1		103	196
US	13	30	22	1	48	485	63	347	144	25	28	35	127	625	21	69	351	236	13	28	17	65	9	8	17	64	24		2,915
$\sum j$	112	46	141	82	62	594	296	460	675	153	118	143	536	1,274	28	201	487	267	69	44	24	206	63	24	31	262	62	4,028	10,488

Note: This table reports the aggregated amount venture capital deals during the observation period from 2000 to 2013 between country pairs. It has to be interpreted as follows. The destination country i in the column receives a venture capital deal inflow from the source country j in the row, respectively j has an outflow to i. For the sake of brevity, only the top quantile of countries in terms of VC activity are reported

Table D.12: Regression Table – Random Effect Probit. Dependent Variable: VC activity between country dyad in at least one year 2000–2012

	Coef.	Sdt. Err.	z	P > z	95% Conf. Interval	
			Distance			
dist cult$_{i,j}$	-5.5647	0.5765	-9.6500	0.0000	-6.6947	-4.4347
dist geo$_{i,j}$	-0.4513	0.0149	-30.2000	0.0000	-0.4806	-0.4220
same legal$_{i,j}$	0.0814	0.0305	2.6700	0.0080	0.0217	0.1411
same border$_{i,j}$	0.2643	0.0695	3.8000	0.0000	0.1281	0.4005
same lang$_{i,j}$	0.0926	0.0427	2.1700	0.0300	0.0089	0.1763
			Trust & Relationship			
trust$_{mean(j)}$	-0.3633	0.0877	-4.1400	0.0000	-0.5352	-0.1913
trade$_{mean(i \rightarrow j)}$	-1.1429	0.3350	-3.4100	0.0010	-1.7995	-0.4862
$\Delta trust_{mean(j-i)}$	0.3950	0.0588	6.7200	0.0000	0.2798	0.5102
			Institutions			
cpi$_{j,mean}$	6.1197	0.2229	27.4600	0.0000	5.6828	6.5565
cpi lowest$_j$	0.5211	0.0619	8.4200	0.0000	0.3998	0.6424
cpi lowest$_j$	-0.2149	0.0717	-3.0000	0.0030	-0.3555	-0.0743
inst. stab$_{mean(j)}$	-0.6133	0.0279	-21.9700	0.0000	-0.6680	-0.5586
$\Delta cpi_{mean(j-i}$	-2.4122	0.1494	-16.1400	0.0000	-2.7051	-2.1193
			Controls			
gdp$_{mean(j)}$	7.6400	0.2418	31.5900	0.0000	7.1660	8.1139
gdp cap$_{mean(j}$	-4.5785	0.2931	-15.6200	0.0000	-5.1530	-4.0041
gdp growth$_{mean(j}$	3.1562	0.2471	12.7700	0.0000	2.6719	3.6405
capitaliation$_{mean(j}$	5.0114	0.5268	9.5100	0.0000	3.9789	6.0438
stocks$_{mean(j}$	-0.0874	0.5809	-0.1500	0.8800	-1.2259	1.0511
emerging$_j$	-0.7343	0.0562	-13.0600	0.0000	-0.8445	-0.6241
emerging$_i$	-1.2545	0.0619	-20.2700	0.0000	-1.3758	-1.1331
$\Delta gdp_{mean(j-i)}$	-4.3361	0.1570	-27.6100	0.0000	-4.6439	-4.0283
$\Delta gdp\ cap_{mean(j-i)}$	3.5252	0.2047	17.2200	0.0000	3.1240	3.9264
$\Delta gdp\ growth_{mean(j-i)}$	-1.2368	0.1742	-7.1000	0.0000	-1.5783	-0.8953
$\Delta capitalization_{mean(j-i)}$	-4.9170	0.4028	-12.2100	0.0000	-5.7064	-4.1275
$\Delta stocks_{mean(j-i)}$	2.0402	0.4378	4.6600	0.0000	1.1821	2.8983
N	26,292					
$R2$	0.4642					
Log pseudolikelihood	-6604.48					

Subscript i indicates the source country, j the destination country
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Paper E

Mapping the (R-) Evolution of Technological Fields – A Semantic Network Approach

Roman Jurowetzki[†] and Daniel S. Hain[†]

[†] *IKE, Department of Business and Management, Aalborg University, DK*

The paper has been published in the
Socinfo 2014 Conference Proceedings. Springer Lecture Notes on Computer Science
Vol. 8851, pp. 359–383, 2014.

The layout has been revised, and a preface not included in the original article has been added.

Abstract

The aim of this paper was to provide a framework and novel methodology geared towards mapping technological change in complex interdependent systems by using large amounts of unstructured data from various recent on- and offline sources. Combining techniques from the fields of natural language processing and network analysis, we are able to identify technological fields as overlapping communities of knowledge fragments. Over time persistence of these fragments allows to observe how these fields evolve into trajectories, which may change, split, merge and finally disappear. As empirical example we use the broad area of Technological Singularity*, an umbrella term for different technologies ranging from neuroscience to machine learning and bioengineering, which are seen as main contributors to the development of artificial intelligence and human enhancement technologies. Using a socially enhanced search routine, we extract 1,398 documents for the years 2011-2013. Our analysis highlights the importance of generic interface that allow ease the recombination of technology to increase the pace of technological progress. While we can identify consistent technology fields in static document collections, more advanced ontology reconciliation is needed to be able to track a larger number of communities over time.*

Keywords: Technological change, transition, technology forecasting, natural language processing, network analysis, overlapping community detection, dynamic community detection

Preface

Conceptual frameworks, as the one I sketch in this thesis, help us understanding complex systems by identifying overall commonalities, rules, and relationships. However, to make them useful beyond scholarly discussions and support evidence based decision making, such a framework's determinants (elements, relations, input and output) have to be quantifiable. While in the first papers of this thesis I provide ample own examples and discuss related work on how to measure elements and their characteristics, their network and interaction pattern within and between finance and research sphere, mapping and measuring elements within the technology sphere represents a more challenging task. In chapter A, I identify a set of interrelated challenges for empirical research in the energy sector representative for a large and complex technological system, where the delimitation of sectors and technologies represents the first necessary condition for empirical work. Indeed, the energy area is vast and diverse, including a multitude technologies from different technological fields and deployed in various industries. Many of those technologies can in a specific configuration be used for the production, distribution, storage and efficient consumption of energy, but originate from and are still deployed for the same or different tasks in other sectors. This prevalent technological diversity represents a major challenge for a delimitation of the energy sector and it's subsystems. Yet, such a delineation of technological systems, subsystems, their components and interactions is fundamental for any descriptive or predictive analysis of technological change and its drivers, including finance. This challenge, even though quite distinct, is not unique to the energy sector but nowadays can be found in many large technological systems. Contemporary trends of modularisation and the emergence of "interface technologies" ease the combination and re-combination of components from different technological trajectories, sectors and paradigms, making the line between different sectors increasingly blurry. Among others, the rapid progress of ICT technology led to its penetration of virtually all areas of social and commercial activity, and the development of common data transfer protocols and interfaces is said to make technologies from different trajectory more compatible with each other.

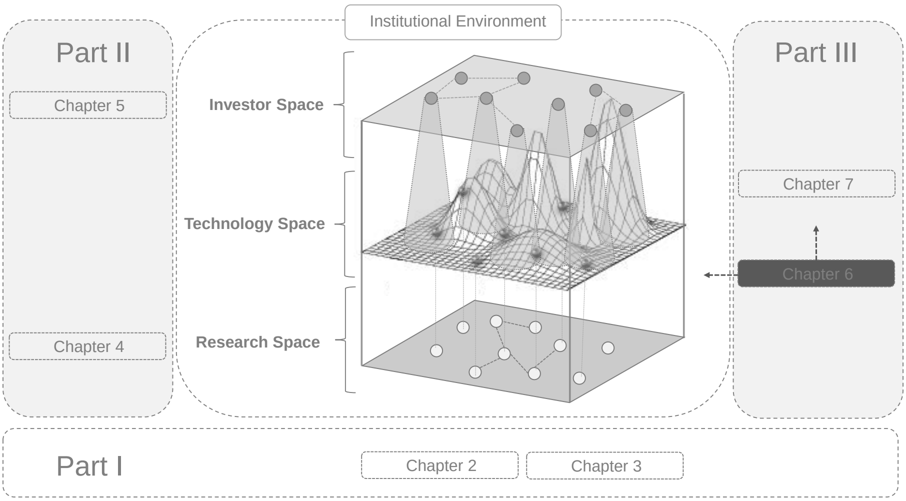
Obviously, static classifications such as industry IPC codes or patent classes are of very limited use to delimit and map such interconnected and rapidly evolving technological systems. Common approaches to do so are mostly limited to qualitative in-depth case studies (Davies, 1996), quantitative methods based on patents (Verspagen, 2007) or scientific publication (Wagner and

Leydesdorff, 2005) data, and more generic simulation models (Dawid, 2006; Lopolito et al., 2013). While undeniably useful, they either require massive effort to qualitatively analyze complex interaction patterns in technological space, or rely on quantitative data only available with non-negligible time delay, and only relevant for certain technology domains, often underestimating the context in which technology is used.

During the last decade we have witnessed tremendous growth of freely available digital information, often in the form of unstructured text data from sources such as web-sites and blogs, written communication of communities in forums or via e-mail, and knowledge repositories (e.g. SSRN, Researchgate). The topicality and sheer amount of such data bear great opportunities for social science research in general, and particularly to timely analyze complex technological change. Most recently, social scientists have also started to deploy methods from the fields of computational linguistic and natural language processing (NLP) to advance empirical research on the development of science and technology (DiMaggio et al., 2013; McFarland et al., 2013; Mohr and Bogdanov, 2013; Ramage et al., 2009). In their essence, such linguistically informed methods are capable of identifying patterns of language usage in large bodies of text and communication.

Taping in this new source and utilizing newest advances in NLP and network analysis, my co-author Roman Jurowetzki and I in this chapter develop a framework and suggest a set of methods geared towards mapping technological change in complex interdependent systems by using large amounts of unstructured text data from various on- and offline sources. Such an approach integrates the broad multidimensional perspective of qualitative researchers with quantitative objectivity given by the machine learning based methodology. To do so, I extract a large number of text documents all over the internet, using a social search routine that we built around the followship structure within the microblogging service twitter. Deploying entity recognition tools from the semantic web area and community detection techniques from modern network analysis, I am able to represent technological systems as a network of functionally related technologies, and identify fields of densely related technologies. By doing so, I am able to observe the evolution of such fields over time, and identify the technological trajectories they follow. I believe this to be a crucial step towards a dynamic and adaptable real-time mapping of technological evolution. I further suggest feasible methods such as entity identification techniques to link these technologies again to actors in the research and finance sphere. Having such tools at hand, in further steps a more nuanced discourse on the interplay of finance and technology beyond the aggregation of investments fitting in certain static classifications is possible. Instead, a dynamic mapping of technological change as the reconfiguration of relationships of technologies enables us to analyze the impact of investments in terms of its contribution to the technological system's evolution in a certain direction.

Fig. E.1: Positioning the paper in the theoretical framework



This chapter mainly attempts to explore the internal dynamics of the technology space in isolation. The main focus lays on developing a method to provide data suitable for mapping , analyzing and predicting technological change, as I do in the following chapter F. Yet, it also offers first insights, particularly on the role densely connected "interface technologies" play in the evolution of technological fields and systems by easing the burden to combine formerly separated technologies. These findings appear suitable for future research that aims to develop predictive models to forecast the emergence of such interface technologies, or even technological revolutions. In addition, I illustrate how entity recognition techniques can be used to easily identify associations between technologies, investors and researchers/firms to establish links between technology, research and finance space

This paper was developed during my visiting researcher period at Stanford University, and simultaneously Roman's research stay at RAND Europe, Cambridge. Exposed to new state-of-the-art methods as well as latest conceptual developments, we combined our insights to develop a new method to tackle important issues in our field of research. It was firstly presented at the Stanford Network Forum 2014, afterwards the ISS 2014 in Jena, and finally at the SocInfo 2014 in Barcelona. It is published in the *Social Informatics Conference Proceedings*, as part of the *Springer Lecture Notes in Computer Science*.

1 Introduction

Understanding the pattern of technological change is a crucial precondition to formulate meaningful long-term research and industry policy. Technological change usually happens along *technological trajectories* Dosi (1982) focusing its pathway within a *scientific paradigm* Kuhn (1962). Apart from defining the boundaries, a paradigm often provides a set of generic *technology artifacts* which can be deployed along multiple trajectories Bresnahan and Trajtenberg (1995). Furthermore, recent trends towards modularization and the development of common interfaces have led to an increasing compatibility of technologies within and between paradigms. We argue that today we face an accelerating deterioration of burdens for technology (re-)combination through growing complementary of components Baldwin and Clark (2000); Schilling (2000). In order to understand innovation activity in many modern technological fields, it therefore becomes pivotal to deploy conceptual frameworks, methods, and data geared towards the analysis of such dynamic and highly interdependent systems.

Common approaches to analyze technological change are yet limited to qualitative in-depth case studies Davies (1996); Hekkert and Negro (2009), quantitative methods depending on data such as patents Verspagen (2007) or scientific publications Wagner and Leydesdorff (2005), and more generic simulation models Dawid (2006); Lopolito et al. (2013). While undeniably useful, they either require massive effort to qualitatively analyze complex interaction patterns in technological space, or rely on quantitative data only available with non-negligible time delay, and only relevant for certain technology domains, often underestimating the context in which technology is used. During the last decade we have witnessed tremendous growth of freely available digital information, often in the form of unstructured text data from sources such as web-sites and blogs, written communication of communities in forums or via e-mail, and knowledge repositories (e.g. SSRN, Researchgate). The topicality and sheer amount of such data bear great opportunities for social science research in general, and particularly to timely analyze complex technological change, as we attempt to demonstrate in the following.

In this paper we present a framework and suggest a set of methods to map technological change by using large amounts of unstructured text data from various on- and offline sources. We conceptualize technological change as the reconfiguration of interaction patterns between *technology fragments*, and their clustering in space to *technological fields*, and in time to *technological trajectories*. To analyze such change, we propose the combination of techniques from the fields of natural language processing (NLP) and network analysis. We use the case of *technological singularity* to illustrate our approach graphically as well as with key measures derived from network analysis.

The remainder of the paper is structured as follows. Section **??** reviews and discusses literature and concepts of technological change, and provides a theoretical framework for our approach. In section 4 we suggest a set of methods suitable to analyze such a framework, and illustrate it in section 5 at the case of *singularity* technologies. Finally, section 6 concludes, provides implications for theory, empirical research, and suggests applications for science and industry policy.

2 Conceptualization and Analysis of Technological Change

2.1 Conceptualization of technological change

The conceptualization of technological change has a long tradition in different academic communities. Generally, technology exists to fulfill or support some societal functions through direct application or indirectly through derived products. It is thus always embedded in and framed by a societal, political and organizational context, which co-evolves with it Kaplan and Tripsas (2008). It is also understood as happening within broader *scientific paradigms* Kuhn (1962).

Scholars studying industrial dynamics further describe the development of technology as contextual to the evolution of industrial structures Dosi (1982); Hain and Jurowetzki (ming). Technology is envisioned as a mean to problem solving in a particular context, which could usually be solved in various other ways using other technologies. *Technological trajectories* represent pathways spanning across the technological space delimited by the paradigm Dosi (1982), focusing the problem solving process over time around one possible configuration of technologies. While this process usually unfolds gradually, sometimes significant technological discontinuities punctuate a trajectory Perez (2010). Such disruptive change radically alters a trajectory's or even paradigm's internal logic, or completely replaces it in an act of Schumpeterian creative destruction Schumpeter (1942). Overall that suggests competition between substitutional trajectories. Yet, they can also be compatible and complementary to each other, since generic technological artifacts may feed the progress of multiple trajectories.

Drawing on work in theoretical biology Kauffman (1993), technological evolution can be conceived as a recombinatory process of novel and existing component technologies within complex adaptive systems Fleming and Sorenson (2001). Innovative recombinations can address fundamentally different problems from the ones that were initially targeted within the components' paradigms. This comes close to a Schumpeterian understanding, where the innovation process is envisioned as the recombination of existing resources in a novel way Schumpeter (1942). The result of such a development can also be envisioned as a complex system with a number of elements that collectively fulfill a single or various goals Simon (1969). A main characteristic of such complex systems is a high degree of interdependence (or epistasis), meaning a functional sensitivity of a system to changes in constituent elements Fleming and Sorenson (2001). Thus, a change in one element will affect not only affect its own but also the functioning of epistatically related ones Frenken (2006). Since the complexity of the system increases with the number of elements and their degree of interdependence, in large epistatic systems one faces a *complexity catastrophe*, making it increasingly hard to find useful combinations Fleming and Sorenson (2001).

A possible solution suggested to avoid the *complexity catastrophe* is to increase the systems modularity Baldwin and Clark (2000); Ethiraj and Levinthal (2004); Schilling (2000). This approach aims at the development of standardized interfaces between more discrete elements to mediate interdependence Langlois (2002), thus allowing to decrease the overall complexity while maintaining the number of possible recombinations. Modularity and common interfaces further ease the way to combine and recombine components stemming from different trajectories, perhaps even different paradigms. On a higher level, technological revolutions disrupting current techno-economic paradigms are usually accompanied by the emergence of such modules, which can be deployed in various contexts Perez (2010). A recent and very obvious example for this development, the smartphone, is illustrated in figure **??**. The combination of voice and data communication with GPS, camera, compass and accelerometer technologies, bound together by a miniature touchscreen-computer, opened up for a uncountable number of not anticipated applications. Various standardized wireless connection technologies like bluetooth or WiFi allow for compatibility with many other external devises, thus increasing the functionality and re-purposing the phone.[1]

[1]The continuation of these dynamics on a higher level of aggregation can be seen in the currently evolving Internet of Things (IoT), where the pairing of everyday objects with sensors and

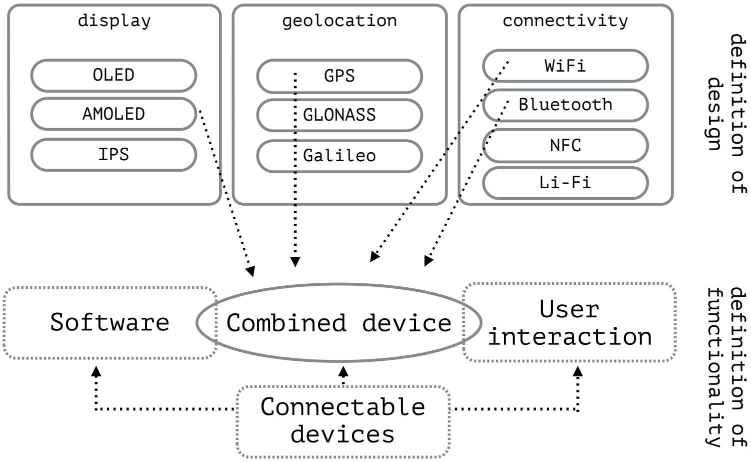


Fig. E.2: Illustrative combination of technology components from different trajectories

We argue that today we are witnessing a rapid decline of the burdens to technology-combination through efficient modularization between components within artifacts such as the smartphone. Embracing this line of thought, we aim to develop a framework and methodology geared towards the analysis of evolving interdependent technology systems. Such a framework has to be able to capture the ongoing incremental adjustment of interaction pattern between its components (*technological evolution*) as well as disruptive changes fundamentally altering the systems logic (*technological revolution*).

2.2 Measurement and analysis of technological change

Existing empirical research on technological change can broadly be divided in three fields. Work from scholars associated with the Science, Technology and Society (STS) tradition mainly relies on detailed ethnographic studies of the complex multidimensional setup around technological systems, and sheds light on the variety of factors that influence and shape its development (Bijker, 1997; Bijker et al., 2012; Hughes, 1987a).

A stream of more positivistic research in the fields of industrial economics and sciencometrics is primarily based on patent and scientific publication data as an approximation for technological development. Research so far mostly incorporates patent data as aggregated numbers to explain differences in scale Pavitt (1982), or in a network representation to explain struc-

communication devises is supposed to enable many new applications in a variety of contexts, and potentially triggering many disruptive innovations Trappeniers et al. (2013).

tural differences Fontana et al. (2009); Verspagen (2007) in the development of technologies across countries and industries. Patent data has also been used to study invention as a recombination process Fleming and Sorenson (2001, 2004); von Wartburg et al. (2005).[2]

Most recently, social scientists have also started to deploy methods from the fields of computational linguistic and NLP to advance empirical research on the development of science and technology DiMaggio et al. (2013); McFarland et al. (2013); Mohr and Bogdanov (2013); Ramage et al. (2009). In their essence, such linguistically informed methods are capable of identifying patterns of language usage in large bodies of text and communication. They range from simple measures of word co-occurrence across documents, corpora and over time **?**, to complex linguistically informed probability model Hall et al. (2008); Nallapati et al. (2011); Ramage et al. (2010).

We perceive the latter as a fruitful way to analyze technological change, implicitly accounting for the socio-economic context in which it is embedded. Such an approach integrates the broad multidimensional perspective of qualitative researchers, that very importantly emphasizes the role of technology users, organizations and governments in innovation processes, with quantitative objectivity given by the machine learning based methodology.

2.3 Technology evolution as structural network change

We conceptualize technology as a system of interdependent components Hughes (1987b) within their respective trajectories of development Dosi (1982). Representing such systems of interacting elements as networks has brought fresh perspectives and insights to the analysis of complex phenomena from the biological to the social sciences Newman et al. (2006). Embracing this approach, we attempt to analyze technological change as the ongoing structural reconfiguration of interaction between elements in a technology network, which allows us to deploy the rich set of network analysis.

On the lowest level of aggregation in a network representing a technological system, one finds what we call *technology fragments*. They represent atomic, non-reducible repositories of scientific/technological knowledge needed to fulfill certain narrow tasks. Scientific, technological and industrial applications such as machines, software and other devices (which we call

[2]However, besides its merits and easy accessibility, there are widely recognized limits in the use of patent data Griliches (1998); Pavitt (1985) such as the high variation of importance across industries and countries, and over time and the long delay between the time research is conducted and the corresponding patent publication.

technological artifacts) combine *technology fragments* in a functional relationship to produce some output. In our previous example, GPS devices, touchscreens and WiFi receivers represent *technology fragments*, which combined in a functional relationship can resemble the smartphone, a *technological artifact*. On a higher level, sets of complementary and substitutional artifacts form a*technological field* (which could be, let's say *mobile applications and devices*). Over time, such fields develop along *technological trajectories*, where accumulated sets of common configuration patterns reproduce over time and set the foundation for further combinations. Again, fragments and artifacts originating from one field might be reconfigured and redeployed in a different field to fulfill the same or even a different purpose. Furthermore, fragments as well as artifacts might not even mainly belong to one field, but be equally employable across multiple fields.

In summary, our conceptualization of technological change, and the suggested methods to analyze it, is based on the following assumptions:

Assumption 1: *Knowledge fragments are atomic, non-reducible repositories of scientific/technological knowledge*

Assumption 2: *Technology fragments can be arbitrary combined and recombined to resemble functional technological artifacts of varying quality*

Having clarified the elements (or edges) in such a network, one has to decide how to measure the functional relationships between them. In our case, identifying technology fragments in unstructured text data, we have to add the following assumption:

Assumption 3*: Co-location of technology fragments in documents imply a functional relationship between them*

3 Measurement of Technological Change – State of the Art

Empirical research on technological change has a long tradition in different academic communities. Generally technology exists to fulfill or support some societal functions through direct application or indirectly through derived products, is thus always embedded in and framed by a societal, political and organizational context, which co-evolves with it Kaplan and Tripsas (2008). Work by sociologists of science within the STS (Science, Technology and Society) tradition, has produced many concepts and valuable insights into processes of systemic technological change Bijker et al. (2012). The work often relies on detailed description of the complex multidimensional setup around the studied technology and sheds light on the variety of factors that (can) influence and shape its development Bijker (1997).

A substantial stream of more positivistic research in the fields of industrial economics and sciencometrics is based on patent data as an approximation for technological development. Research so far mostly incorporates patent data as aggregated numbers to explain differences in scale Pavitt (1982), or in a network representation to explain structural differences Fontana et al. (2009); Verspagen (2007) in the development of technologies across countries and industries. Patent data has also been used to study invention as a recombination process Fleming and Sorenson (2001, 2004); von Wartburg et al. (2005).[3] Alternatively, similar research also utilizes the assessment by industry experts to delimit and quantify development within and across technologies Pavitt (1984). Carlsson et al. (2002), suggest for instance the use of industry experts to delineate technological systems.

Most recently, social scientists have also started to deploy methods from the fields of computational linguistic and natural language processing to advance empirical research on the development of science, technology and other bodies of knowledge In their essence, such linguistically informed methods are capable of identifying patterns of language usage in large bodies of text and communication. They range from simple measures of (raw or somewhat weighted) word co-occurrence across documents, corpora and over time **?**, to complex probabilistic language and topic identification models Hall et al. (2008), which lately started to gain traction in the social science DiMaggio et al. (2013); McFarland et al. (2013); Mohr and Bogdanov (2013); Ramage et al. (2009). Such models basically identify larger topics by fitting a linguistically informed probability model which tries to predict them using text and meta information of the corpus under investigation. Such topics by nature are rather descriptive and aims to understand how language is used by a certain set of actors to describe and differentiate real-life phenomena. For instance, the interesting variety of lead-lag models which groups of actors, such as universities Ramage et al. (2010) or outlets Nallapati et al. (2011) influence the formation of topics, and which adapt instead.

[3]However, besides its merits and easy accessibility, there are widely recognized limits in the use of patent data Griliches (1998); Pavitt (1985) such as the high variation of importance across industries and countries, and over time and the long delay between the time research is conducted and the corresponding patent publication.

4 Analyzing Technology Evolution: Dynamic Semantic Network Approach

After providing a conceptual framework to analyze technological change, in this section we suggest a set of methods to empirically study such changes. A illustration of the method pipeline is provided in figure **??**.

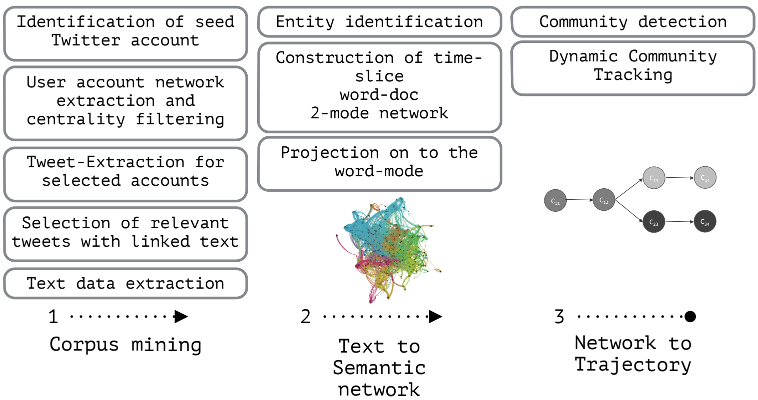


Fig. E.3: Illustration of the method pipeline

4.1 From unstructured text to technology fragments: Entity extraction

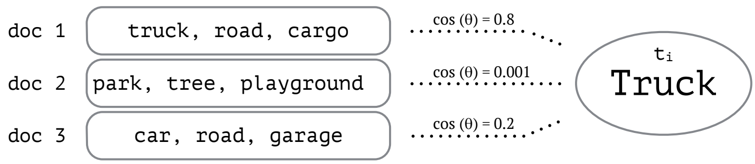
First obvious choice to be made is which corpus of technology related text documents one wants to analyze. Such a corpus should optimally (i.) consist of technology related writings (ii.) ranging equally distributed over a time sufficient to observe technological change, and (iii.) not be biased towards particular technologies within the system. Examples for such data are scientific publications, patent descriptions, articles in industry journals, but also online sources such as collections of tech-blogs. In figure **??** we illustrate how to generate an online data corpus with socially enhanced web scraping techniques.

In a next step, it is necessary to convert the unstructured text documents to a machine readable representation.[4] For our means, the goal is to reduce

[4] Typically, this takes the format of a bag of words (BOW), a line-up of thematically relevant keywords, usually nouns and bi-gram noun phrases. The key assumption of this type of NLP applications is that statistically significant co-occurrence patterns of concepts across the corpus is indicative for actual association between them.

each document to the contained technological concepts. Instead of using a probabilistic approach that stepwise excludes text-elements that are definitely not a technology, we try to detect mentioned technologies in the data. This task falls into the category of *named entity extraction*, which typically relies on tagged dictionaries and string-matching rules to identify the required concepts.

Fig. E.4: Example of pairwise semantic similarity between terms and documents



A number of applications related to this development target the identification of different concepts in unstructured text, among others technological and industrial terms. The advantage of these semantic web tools is that they are supported by large, centralized, constantly updated and optimized dictionaries and intelligent disambiguation functions. The result of a successful entity extraction returns a collection of documents that only contain the mentioned technology terms and their document appearance frequency. Referring to our conceptual framework in section **??**, the extracted technology term resemble the elements (nodes) in our technological system, which we label as *technology fragments*.

4.2 From technology fragments to a network: Vector space modelling

In a first step, one could create a network with the corpus documents as nodes, then vector space modeling and represent them as vectors defined by the respective combination of contained concepts. This representation allows to calculate pairwise similarities between the documents. The result is a fully connected weighed network with documents as nodes and corresponding similarities as edges. Now clustering or community detection algorithms can be used to identify technological fields, represented by document communities discussing them, as suggested by Jurowetzki (2014). Yet this approach has two disadvantage: First, technology fragments are only indirectly represented in networks as node characteristics, what means that many powerful measures in network analysis (such as centrality, betweenness, etc.) are not directly available to describe them, but only the documents containing them.

Second and related, nodes representing documents are not suitable for a dynamic analysis, since they are only associated with one observation period. Thus, one can either construct a cumulative network that only grows, or a network with a complete node turnover every period. For that reasons we have chosen to *liberate* the terms from their *document boundaries* while maintaining the latent semantic similarity structure that is defined by their co-occurrence in documents.

After having defined the nodeset in our network of *technology fragments*, we have to create weighted edges between them, representing their technological relatedness and interaction. In a first step we construct a (hierarchical) 2-mode network between *technology fragments* and the corresponding documents they occur in. We weight the edges by the pairwise cosine similarity between the vectors of the *technology fragment* and document within a vector space, which we define by by training a Latent Semantic Indexing (LSI) model Deerwester (1988); Deerwester et al. (1990) on the full corpus of documents.[5] Thus, our measure of edge weight indicates to which extent the term representing the *technology fragment* is semantically close to the entirety of other terms contained by the document (see figure **??**). To map technological change over time, we do this separated for every observation period.

While the entirety of *technology fragments* is stable over time, documents obviously experience a 100% turnover in population every observation period. To coerce a stable nodeset, we project the 2-mode to a weighted 1-mode network in technology space. Again, the underlying rationale is based on the assumption that co-occurrence in documents - at least on an aggregated level - also corresponds to a functional relationship between *technology fragments*. However, on a document level that will not always be true. While some documents may discuss technology in the realm of one particular *technological fields*, others might serve more as an overview on industry or research of a broader context, hence contain a collection of *technological fragments* from many otherwise distinct fields. Thus, we penalize documents containing more technology fragments in a similar spirit as the method used by Newman (2001), represented by the following equation Opsahl (2013). Here w_{ij} represents the edge-weight between node i and j, and p the corresponding documents.

[5]Before training the model, we apply TF-IDF weights to all terms within the documents. This appreciates the value of particularly important terms for the single document, while depreciating the value of generic terms that often occur across the corpus. Here we have chosen the established LSI algorithm for training the vector space model but other algorithms e.g. Latent Dirichlet allocation (LDA) or Random Projections would also be feasible to calculate pairwise cosines.

$$w_{ij} = \sum_{p} \frac{w_{i,p}}{N_p - 1} \tag{E.1}$$

We end up with a one-mode network of *technology fragments* connected by the pairwise projected semantic similarity values, associated with the corresponding period. Figure E.5 illustrates these nodeset properties in dynamic networks.

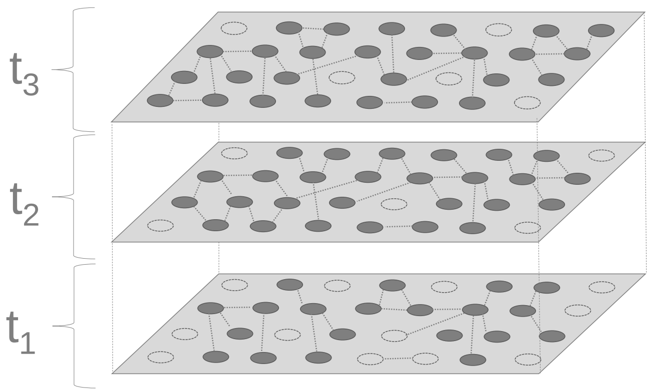


Fig. E.5: Illustration of the development of a nodeset over time

Identifying technological fields: Overlapping community detection

We depict technological change as the structural reconfiguration of micro level interactions between *technology fragments*. When analyzing the structure, function, and dynamics of networks, it is extremely useful to identify sets of related nodes, known as communities, clusters, or partitions Radicchi et al. (2004). Such communities of closely connected technologies resemble what we call a *technological field*, a set of complementary or substitutional technologies following one *technological trajectory*, and clustering over time around a common objective. Therefore, we attempt to identify *technological fields* using a community detection algorithm of choice.[6]

[6] An alternative approach would be to use to identify technological fields by the using topic modeling, an approach that lately started to gain traction in social science DiMaggio et al. (2013); Hall et al. (2008); McFarland et al. (2013), create a two-mode network of terms and topics, and project it to an one-mode network of terms. However, for reasons described we here want to offer an alternative, where the topics are already identified using the powerful community detection methods offered by network analysis.

Early clustering and community detection algorithms, in network analysis and elsewhere, usually assumed that the membership of entities to one distinct group. However, depending on the meaning of edges and nodes, many real life networks show a high overlap of communities, where nodes at the overlap are associated with multiple communities. This especially tends to happen when relationship of different quality are projected in a one-mode network Kivelä et al. (2013). Ones' social interaction network for instance may consist of family members, work colleagues, members of the same karate club or other associations. The more diverse interests such a person has, the more different communities this person will be assigned into. In the same way, the more generic the nature of a *technology fragment* or artifact, the more technological fields will it have functional relationships with. Some *technological artifacts* (and the *technology fragments* resembling them) are that pervasive, they facilitate almost all other technologies in the way they work, such as by its time steam-power or nowadays semiconductors Perez (2010). Embracing that line of thought, researchers recently stated to develop community detection algorithms able to cope with overlapping and nested community structures Ahn et al. (2010); Mucha et al. (2010), which can be deployed to properly delimit interdependent *technological fields*.

Identifying technological trajectories: dynamic community detection

Technological fields do not spontaneously appear and reassemble in a vacuum. They gradually change, grow or decline in an cumulative manner, following a historical *technological trajectory* which connects them over time. However, in times of disruptive technological change, former technology interaction pattern might completely reconfigure, particular new configurations might spin-off a main trajectory and so forth. Owing respect to the evolutionary nature of technology, we want to identify communities which are somewhat stable and thus to be found in multiple observation periods, but also allow *technological fields* to experience disruptive key-events in their life-cycle. Besides helping us linking changing communities over time, the identification of such effects in itself represents an interesting information. We consider the following significant events a community might experience during its evolution, also illustrated in figure **??**:

- Birth & Death: The first time a community C_i^t (which are the representation of a *technological field*) is observed and not matched with an already existing community C_j^{t-1}. This community, however, does not have to be stable over time. We in fact expect a substantial share of communities to only appear in on period but not sustain.

- Pause: Communities might be more stable than the reporting on them in the corpus.Thus, allowing them to pause for a period might smoothen birth & death dynamics.

- Merge: In case two communities develop substantial functional interdependence, the main interaction with the rest of the system only happens between them. Thus they merge and form a new community consisting of both sets. Technically that happens when two or more different communities are matched with one dynamic community D_j in the previous period.

- Split: In the same manner, communities can also separate into independent disciplines. Technically a split occurs when one community C_i matches with two or more dynamic communities in the previous period.

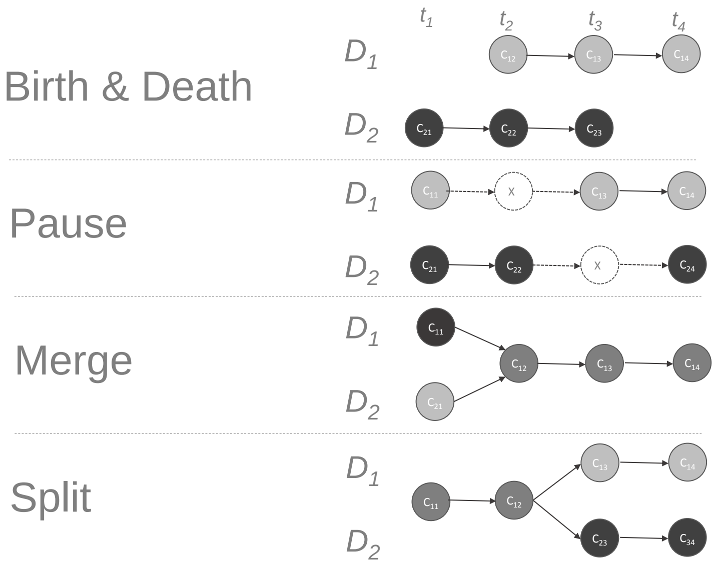


Fig. E.6: Illustration of significant events in the evolution of communities, adopted from Greene et al. (2010)

We do so by applying a simple but effective heuristic threshold-based method allowing for many-to-many mappings between communities across different observation periods proposed by Greene et al. (2010). Here we compare an identified community C_i^t in observation period t with the set of dynamic communities in the previous period $\{C_1^{t-1}, \ldots, C_J^{t-1}\}$ by employing the widely adapted Jaccard coefficient J_{ij}^t, calculated as follows:

$$J_{ij}^t = sim(C_i^t, C_j^{t-1}) = \frac{|C_i^t \cap C_j^{t-1}|}{|C_i^t \cup C_j^{t-1}|} \tag{E.2}$$

If the similarity exceeds the defined matching threshold $\theta \in [0,1]$, both communities are added to the dynamic community D_i. Using this has the advantage that is independent of the (static) community detection method of choice in the observation periods, hence represents a somewhat modular approach. It can also handle overlapping as well as (with some minor adjustments) weighted communities. A major advantage of this approach is the separation of static and dynamic community detection is the high flexibility in the choice of suitable algorithms.

5 Demonstration Case

In the following section we demonstrate the capabilities of our approach to deliver insightful results, and provide some illustrative examples of measures and graphical representations that can be used to gain further insights. We intended to find an empirical case of technological development that would combine a large number of components from traditionally disconnected *technological fields*. Additionally, the *technology field* in focus should be yet in a formative stage and have a potentially strong and broad social impact to generate enough attention and thus reporting texts online. We decided to explore the field of *singularity*. Rather then a clearly delineated *technological field*, singularity represents a future scenario and an umbrella term that summarizes a number of developments in areas as diverse as neuroscience and 3D printing. Based on the context of the technology under study and the characteristics of the corpus, we provide examples how to calibrate the techniques used in the different stages of or method pipeline.

5.1 Empirical setting: The *singularity* case

Technological Singularity as a term has gained momentum since the publication of Ray Kurzweil's book in 2005 Kurzweil (2005). Observing various measures of technological progress over time, he argues that most technologies improved their performance exponentially and therefore it is only a matter of a few decades until we will have reached a point in history when artificial intelligence will supersede human intelligence. The most powerful technological advancement of the 21th century will happen when robotics, nanotechnology, genetic engineering and artificial intelligence reach a certain level of development and can be combined, what will have disruptive consequences for society, culture and the human nature. Overall, the literature describes two possible (perhaps even simultaneously possible) scenarios: The first scenario is the rise of engineered super-intelligent agents that might even become a threat to humanity Joy (2000). A more cheerful scenario is advocated by the *transhumanists*. Here the focus is more on the evolution of human enhancement technologies that will improve human physical an cognitive abilities and in the long run might contribute to the rise of a post-human society Eden et al. (2013). While many of the forecasts sound like science fiction, others seem plausible.

Recently, *singularity* entered the European technology policy context, as a technological field within the Horizon 2020 programming. Since 2012, the Directorate General for Communications Networks, Content and Technology (DG CONNECT) is undertaking a foresight process to inform the ICT related programming of research to be financed under Horizon 2020, where *singularity* was identified as one of the 10 central technological fields. It is currently being examined closer to capture early signals and anticipate beneficial trends that should be supported within public research funding schemes.

5.2 Data mining & corpus generation

Researchers, organizations and science journalists are increasingly using social media and the blogosphere to communicate findings and developments, far ahead of journal publication or conference proceedings. This makes microblogging platforms and in particular Twitter with over 200 million monthly active users (Feb. 2014) a valuable source of data. We now describe our data mining approach aiming at selecting relevant twitter updates by relevant users. Instead of using already available corpora to study technological change in *singularity*, such as patent description, scientific publications and industry journals, we choose to create an own out of a variety of online available technology relevant text documents, including publications, tech-blogs *et cetera*. Since *singularity* is a recent and very heterogeneous movement spanning various scientific, industries and tech-communities with distinct routines for communicating and publishing findings and progress, our final corpus therefore is supposed to be unbiassed towards a particular discipline.

To identify relevant documents, we employ a socially-enhanced search routine based on twitter tweets. [7] Twitter's graph structure, built on followship links, is similar to citation networks in academic publications. This enables the construction of large directed graphs and allows applying network analysis methods, to identify central actors for a particular field or topic. For this study we constructed a large followship graph around the - somewhat arbitrarily selected - account *Singularity Hub*, which is an online news platform that actively reports on the topic. The initial *snowballed* network has 49,574 accounts. Using eigenvector centrality, we identify the most influential users and then manually reduce the number of nodes down to 34 twitter accounts that indicate an interest for the area in their profile.[8] Figure **??** shows a central fragment of the network. Coloring represents communities, detected by the Louvain algorithm Blondel et al. (2008), merely for illustration. We can see that the red cluster seems to contain all the central organisations that are present on twitter and focused on singularity and transhumanism like the H+ movement, KurzweilAI, David Orban and more. The green cluster is mostly populated with users that are related to robotics and the violet to software architecture. An overview of the selected user accounts can be found in figure **??**.

Micro-blogged tweets (status updates) by these actors often contain links to research papers, popular media articles or blog entries that the selected user considers as worth communicating. For each of these accounts we extract up to 3,200 status updates starting with the most recent, 63,000 in total. We discard all updates that do not carry a link. Relevant tweets were then identified using a vector space model powered semantic search. The data search thus becomes to a certain degree socially enhanced as opposed to the results of search engines, which are more likely to return most popular or sponsored rather than relevant results. The text content behind the embedded links - outside of Twitter – is then extracted and processed, and finally represents our document corpus for further analysis.

An often used methodology for BOW transformation combines part of speech tagging (POS), n-gram detection, stopword elimination, various types of term frequency filtering and language normalisation such as stemming or lemmatisation. Such an approach is very fruitful for the detection of multidimensional themes in unstructured data, for instance in news-summarization

[7] However, our socially-enhanced approach only illustrates possibilities of corpus generation. Our general methodology is, mutatis mutandis, able to handle various sources of input of technology relevant text documents.

[8] This selection is very restrictive but is likely to make the final corpus less noisy. Alternatively the manual reduction can be skipped and a corpus filtering built in, at a later stage.

tasks. Here, various types of interacting objects (e.g. locations, persons, organizations etc.) contribute to the construction of events and backgroundstories. The selection of the keywords does not rely on predefined dictionaries and can therefore be very permissive, meaning that novel concepts would rather be included if they fulfill certain linguistic criteria. Initially, we tried to apply this approach for out means, but decided to discard it, as the generated BOW representations were to noisy. While many of the included concepts could be associated with technologies, there were too many other unrelated terms that would distort the analysis.

5.3 Identification of technology fragments: Entity extraction

The documents in our corpus discuss technology from very different angles. Some talk about state-of-the art research in certain university labs, while others review the allocation of public research grants or venture capital investment strategies. When attempting to uncover functional relationships between technology fragments, it is crucial to avoid false positives caused by relationships that are non-technical in nature, such as *being funded by the same investor*, or *developed in the same country*. More traditional statistical NLP approaches to BOW generation, including Part of speech tagging and n-gram detection are useful when large pieces of text data have to be reduced to relevant keywords that summarize the essence of the particular document. Yet, when using network analysis to investigate relationship structures between terms, one has to make sure only including relationships of interest. In this case, restricting the nodeset carefully to identified technology terms is one attempt to do so. We rely on entity extraction when condensing documents to BOW representations. In the particular case we use OpenCalais, a free web service that performs entity identification across 39 different concepts within submitted text data. The great advantage of *cloudsourcing* in this case is given by the fact that the centralized machine learning algorithms of OpenCalais are trained on a very large amount of natural text and its dictionaries are constantly updated and optimized. An offline solution would hardly be able to compete in terms of performance and topicality.[9] When inspecting the results we find clear technology terms such as *dna profiling*, *robotic surgical systems*, *clinical genomics* or *regenerative stem cell technologies*, which come

[9]For an overview and performance evaluation of available systems see Rizzo and Troncy (2011). In addition, OpenCalais provides ontology reconciliation and disambiguation. Identified entities are in many cases enriched with metadata (e.g. profession for persons, ticker symbols for companies and geospatial coordinates for locations). Other detected entity types are not used in this analysis.

fairly close to how we understand technology fragments. These terms narrowly describe technology deployed for a fairly delimited task. However, we also find boarder technology terms such as *stem cells genomics*, which span across a somewhat larger field of applications and are likely to include some of the aforementioned terms, and on an even more generic level terms such as *biotechnology* or *robot*.[10] While this clearly diverts from our theoretical framework, where we find on node level only functional interaction of atomic *technology fragments*, we do not consider that as worrisome for the analysis to come.

5.4 Network generation, technological field & trajectory identification

For a very first inspection and illustration of the nodeset we create a simple static network of all documents connected by their similarity in terms of containing *technology fragments*, cluster them by applying the common Louvain algorithm Blondel et al. (2008), and plot them in figure **??**. For the three main communities detected we provide a tag-cloud, weighted by the fragments' TF-IDF scores. One can see at first glance that our *singularity* corpus very broadly consists of three fields, where the biggest is centered around robotics, and the two others around (stem) cell and brain research, or to be more interpretative: Robotics, biotechnology and neuroscience. Figure **??** provides some key statistics on the networks, communities, and their development. While subject to some fluctuation, the networks seem to develop from many to less nodes and edges, and to less but denser communities. This might indicate *singularity* after an initial phase of experimentation to mature and establish more delimited fields and sub-disciplines, as life-cycle theories might suggest.

We now construct a set of two-mode networks between this nodes and the documents in our corpus,[11] containing only documents published in the corresponding observation period, which we choose to be half a year.[12] Fi-

[10] In future iteration of this approach, a more conservative filtering of high-frequency contextual stopwords might decrease the presence of too general terms.

[11] Vector space modeling is performed with the GENSIM package Řehůřek and Sojka (2011) within IPython, using LSI and a 400 dimensional model as suggested by Bradford (2008)

[12] This choice has to be made according to the properties of the data to be analyzed, since best results can be achieved when the network structure shows some gradual change between the observation periods, but no radical turnover suggestion complete discontinuity. This corresponds roughly to a Jaccard index of the two networks between 0.2 and 0.8.

nally, we project this structures on one-mode networks between technology fragments.

Now we identify *technological fields* with the link community detection algorithm proposed by Ahn et al. (2010), which is able to detect communities with highly pervasive overlap by clustering links between the nodes rather than the nodes themselves.[13] Each node here inherits all memberships of its links and can thus belong to multiple, overlapping communities (*technological fields*). By doing so, we owe respect to the overlapping and nested structure of technology, and are able to identify key *technological fragments* interacting with multiple distinct fields.[14] We first run the community detection separated for every time step independently. We do not *a-priori* define a fixed amount of communities, but rather set the cutoff at the point where the average community density is optimized in every observation period.

Figure **??** plots the network of *knowledge fragments* and their membership to *technological fields* for every timestep. Again, what can be seen is that *singularity* appears to develop from a broad area without clear boundaries and high interconnectedness towards clearly delimited *technological fields*. However, we also find first hints that over time some very generic technologies such as *smartphones* and *artificial intelligence* appear to develop towards a very central position, where they serve as common interface between most other fields. While it seems unlikely that *smartphones* (as we understand them today) will be around for much longer then a decade, their centrality in the singularity discussion can be understood as the importance of mobile devices that enhance our by nature limited interaction range. In fact, *smartphones* became a rapidly adopted human enhancement device and currently a number of different wearable technologies are entering the mainstream markets. We also see the generic *artificial intelligence*, which is at the very core of the singularity debate, in a very central position as interface or generic technology between *technological*.

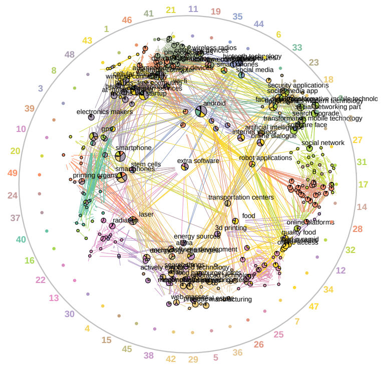
We now perform a threshold-based dynamic community detection[15], where we besides an immense turnover of briefly appearing and disseminating short-term trends indeed find identify a set of persistent *technological trajectories*. Figure **??** illustrates the composition of some selected communities

[13]We use the implementation of the link-community approach provided by Kalinka and Tomancak (2011) as package for the statistical environment R.

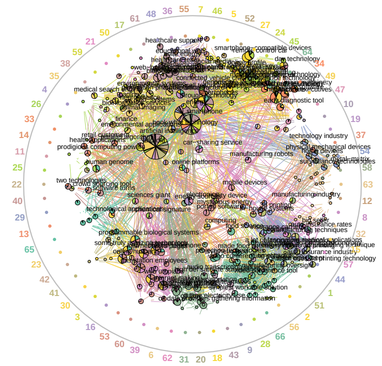
[14]Most traditional community detection algorithms would in the above described case of high overlap detect communities somewhat resembling a core-periphery structure, with a central highly interconnected community surrounded by sparsely interconnected ones, where link communities allow for the multi-group membership of nodes.

[15]We use a C++ implementation provided by Greene et al. (2010)

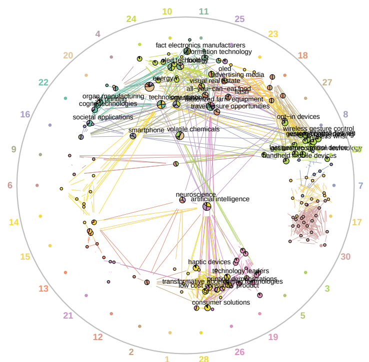
Table E.1: Network of Knowledge Fragments per Period after Overlapping Community Detection



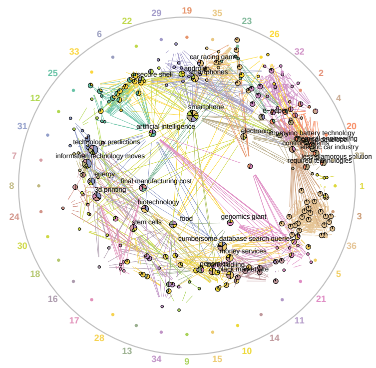
2012, 1^{st}



2012, 2^{nd}



2013, 1^{st}



2013, 2^{nd}

Nodes are aligned according to their main community, represented by the number outside the circle. Node size is scaled by number of communities the node belongs to. Multi-community membership is also indicated by multiple node color

Table E.2: Exemplary identified technological fields and their knowledge fragments

Biometrics & Law Enforcement

Ubiquity & Social Networks

Genomics

3D Printing

Nodes term representing the name of the technology fragment represented as tag-cloud. Size weighted by the nodes within community degree centrality.

which proves to be somewhat stable over time.[16] The tag-cluster are a good way to visualize the interaction between the actual technologies, principal applications and challenges. The first cluster suggests for instance that an important area of application for biometric technologies in conjuncture with machine learning will be found within law enforcement. The second cluster addresses advancements in the area of augmented reality and connections to existent social network structures using primarily mobile devices.

6 Summary and Conclusion

The aim of this paper was to provide a framework and novel methodology geared towards mapping technological change in complex interdependent systems by using large amounts of unstructured data from various recent on- and offline sources. We combine techniques from the fields of NLP and network analysis. Our approach is based on the following steps:

- Using entity recognition techniques we identify technology related terms in the text document of our corpus, which resemble *technology fragments*.
- In a first step, using vector space modeling, we construct an undirected two-mode network between technology fragments and corpus documents for every observation period, where the edges are weighted by the pairwise cosine similarities between documents and terms.
- After projecting this network in technology space, we end up with an undirected one-mode network of technology fragments connected by their weighted co-occurrence in documents of the corresponding observation period.
- To delimit *technological fields* in every observation period, we use overlapping community detection techniques, owing respect to the interdependent and nested nature of technology.
- To identify *technological trajectories*, we link *technological fields* between observation periods over time using

As empirical example we use the broad area of *Technological Singularity*, a umbrella term for different technologies ranging from neuroscience to machine learning and bioengineering which are seen as main contributors to

[16]For the sake of clarity, the technology fragments are weighted by their within-cluster centrality.

the development of artificial intelligence and human enhancement technologies. We extract 1,398 relevant text documents all over the internet, using a social search routine that we built around the followship structure within the microblogging service twitter. Using entity recognition tools from the semantic web area, we reduce documents to technology-term representations and finally generate a semantic timestep network of technology fragments. Our community detection exercise identified many coherent technological fields within each community. Already the static clustering provides valuable insights in the emergence of new technological fields and applications for existing technologies. Overlapping community detection, allowed us also to identify certain *general* technologies that work as hubs between other technologies, stemming from a large number of different domains.

Yet, we find the results of the community-tracking over time unsatisfactory. The obstacle are *false negatives* that obstruct the identification of similar communities over time. While we, as humans, can see that very similar communities are present in successive timesteps, even though the contained terms are slightly different, the algorithm is unable to identify this because the terms are not identical. Our language is full of synonyms, metaphors and unregulated terminology. The reader of this article has no difficulty comprehending that we use the terms *clusters* and *communities* interchangeably, a computer would not. While we are (yet) unable to *teach* the algorithm a deep understanding of ontology, we can try to normalize the terminology as far as possible. This future measure should increase the number of identical terms over time. Furthermore, there seem to be a trade-off between the thematic scope of a given corpus and the resolution of the analysis. Therefore, a broader corpus is most suitable for creating a broad-brush picture of technological change. Another measure to normalize the language would be to chose a less noisy corpus. Single scientific and technological fields tend to have a relatively homogeneous terminology. Therefore we believe that the proposed method combination will perform better on the atomic level if the corpus is more focused on a particular technology or scientific field.

We believe a major advantage of our approach is that it conveys text data into a network representation suitable for a dynamic analysis of technology. It proves to be more flexible with respect to the corpus than other semantic or n-gram based methods in natural language processing. Furthermore, for subsequent quantitative analysis and graphical representation one can now draw from the large toolkit of powerful methods available for network analysis. The here performed dynamic community detection is one example, but other methods such as blockmodeling appear to be promising to gain further insights into the evolution of technology. Finally, networks are well established in many areas of social science and thus a representation of semantic features as networks is likely to help bridging the gap between scholars in computer and social science.

References

Ahn, Y.-Y., Bagrow, J. P., and Lehmann, S. (2010). Link communities reveal multiscale complexity in networks. *Nature*, 466(7307):761–764.

Baldwin, C. Y. and Clark, K. B. (2000). *Design Rules: The power of modularity*. MIT Press.

Bijker, W. E. (1997). *Of Bicycles, Bakelites and Bulbs*. Toward a Theory of Sociotechnical Change. The MIT Press.

Bijker, W. E., Hughes, T. P., Pinch, T., and Douglas, D. G. (2012). *The Social Construction of Technological Systems*. New Directions in the Sociology and History of Technology. MIT Press.

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., and Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10):P10008.

Bradford, R. B. (2008). An empirical study of required dimensionality for large-scale latent semantic indexing applications. In *Proceeding of the 17th ACM conference*, page 153, New York, New York, USA. ACM Press.

Bresnahan, T. F. and Trajtenberg, M. (1995). General purpose technologies 'engines of growth'? *Journal of econometrics*, 65(1):83–108.

Carlsson, B., Jacobsson, S., Holmén, M., and Rickne, A. (2002). Innovation systems: analytical and methodological issues. *Research Policy*, 31(2):233–245.

Davies, A. (1996). Innovation in large technical systems: the case of telecommunications. *Industrial and Corporate Change*, 5(4):1143–1180.

Dawid, H. (2006). *Agent-based models of innovation and technological change*, volume 2, chapter 25, pages 1235–1272. Elsevier.

Deerwester, S. (1988). Improving information retrieval with latent semantic indexing. *In Proceedings of the 51st ASIS Annual Meeting (ASIS 8́8), Vol. 25 (October 1988)*, 25.

Deerwester, S. C., Dumais, S. T., Landauer, T. K., Furnas, G. W., and Harshman, R. A. (1990). Indexing by latent semantic analysis. *JASIS*, 41(6):391–407.

DiMaggio, P., Nag, M., and Blei, D. (2013). Exploiting affinities between topic modeling and the sociological perspective on culture: Application to newspaper coverage of us government arts funding. *Poetics*, 41(6):570–606.

Dosi, G. (1982). Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11(3):147–162.

Eden, A. H., Moor, J. H., Soraker, J. H., and Steinhart, E. (2013). *Singularity Hypotheses*. A Scientific and Philosophical Assessment. Springer.

Ethiraj, S. K. and Levinthal, D. (2004). Modularity and innovation in complex systems. *Management Science*.

Fleming, L. and Sorenson, O. (2001). Technology as a complex adaptive system: evidence from patent data. *Research Policy*, 30(7):1019–1039.

Fleming, L. and Sorenson, O. (2004). Science as a map in technological search. *Strategic Management Journal*, 25(89):909–928.

Fontana, R., Nuvolari, A., and Verspagen, B. (2009). Mapping technological trajectories as patent citation networks. an application to data communication standards. *Economics of Innovation and New Technology*, 18(4):311–336.

Frenken, K. (2006). A fitness landscape approach to technological complexity, modularity, and vertical disintegration. *Structural Change and Economic Dynamics*, 17(3):288–305.

Greene, D., Doyle, D., and Cunningham, P. (2010). Tracking the evolution of communities in dynamic social networks. In *Proc. International Conference on Advances in Social Networks Analysis and Mining (ASONAM'10)*.

Griliches, Z. (1998). Patent statistics as economic indicators: a survey. In *R&D and productivity: the econometric evidence*, pages 287–343. University of Chicago Press.

Hain, D. S. and Jurowetzki, R. (forthcoming). Incremental by design? on the role of incumbents in technology niches - an evolutionary network analysis. *Journal of Evolutionary Economics*.

Hall, D., Jurafsky, D., and Manning, C. D. (2008). Studying the history of ideas using topic models. In *Proceedings of the conference on empirical methods in natural language processing*, pages 363–371. Association for Computational Linguistics.

Hekkert, M. P. and Negro, S. O. (2009). Technological forecasting & social change. *Technological Forecasting & Social Change*, 76(4):584–594.

Hughes, T. P. (1987a). *The Evolution of Large Technological Systems*, pages 51–82. The MIT Press.

Hughes, T. P. (1987b). The evolution of large technological systems. *The social construction of technological systems: New directions in the sociology and history of technology*, pages 51–82.

Joy, B. (2000). Nanoethics: The ethical and social implications of nanotechnology - google books. *Nanoethics–the ethical and social implicatons of ...*.

Jurowetzki, R. (2014). Exploring technology evolution in danish smart grid development - an nlp approach. In *DRUID Academy Conderence*, pages 1–25.

Kalinka, A. T. and Tomancak, P. (2011). linkcomm: an r package for the generation, visualization, and analysis of link communities in networks of arbitrary size and type. *Bioinformatics*, 27(14).

Kaplan, S. and Tripsas, M. (2008). Thinking about technology: Applying a cognitive lens to technical change. *Research Policy*, 37(5):790–805.

Kauffman, S. A. (1993). *The Origins of Order*. Self-Organization and Selection in Evolution. Oxford University Press.

Kivelä, M., Arenas, A., Barthelemy, M., Gleeson, J. P., Moreno, Y., and Porter, M. A. (2013). Multilayer networks. *arXiv preprint arXiv:1309.7233*.

Kuhn, T. S. (1962). *The Structure of Scientific Revolutions*. University of Chicago Press.

Kurzweil, R. (2005). *The Singularity Is Near*. When Humans Transcend Biology. Penguin.

Langlois, R. N. (2002). Modularity in technology and organization. *Journal of Economic Behavior and Organization*.

Lopolito, A., Morone, P., and Taylor, R. (2013). Emerging innovation niches: An agent based model. *Research Policy*, 42(6):1225–1238.

McFarland, D. A., Ramage, D., Chuang, J., Heer, J., Manning, C. D., and Jurafsky, D. (2013). Differentiating language usage through topic models. *Poetics*, 41(6):607–625.

Mohr, J. W. and Bogdanov, P. (2013). Introduction - topic models: What they are and why they matter. *Poetics*, 41(6):545–569.

Mucha, P. J., Richardson, T., Macon, K., Porter, M. A., and Onnela, J.-P. (2010). Community structure in time-dependent, multiscale, and multiplex networks. *Science*, 328(5980):876–878.

Nallapati, R., Shi, X., McFarland, D. A., Leskovec, J., and Jurafsky, D. (2011). Leadlag LDA: Estimating topic specific leads and lags of information outlets. In *ICWSM*.

Newman, M. (2001). Scientific collaboration networks. ii. shortest paths, weighted networks, and centrality. *Physical review*, 64(1):016132.

Newman, M., Barabási, A.-L., and Watts, D. J. (2006). *The Structure and Dynamics of Networks:*. Princeton University Press.

Opsahl, T. (2013). Triadic closure in two-mode networks: Redefining the global and local clustering coefficients. *Social Networks*, 35(2):159–167.

Pavitt, K. (1982). R&d, patenting and innovative activities: a statistical exploration. *Research Policy*, 11(1):33–51.

Pavitt, K. (1984). Sectoral patterns of technical change: towards a taxonomy and a theory. *Research policy*, 13(6):343–373.

Pavitt, K. (1985). Patent statistics as indicators of innovative activities: possibilities and problems. *Scientometrics*, 7(1):77–99.

Perez, C. (2010). Technological revolutions and techno-economic paradigms. *Cambridge Journal of Economics*, 34:185–202.

Radicchi, F., Castellano, C., Cecconi, F., Loreto, V., and Parisi, D. (2004). Defining and identifying communities in networks. *Proceedings of the National Academy of Sciences of the United States of America*, 101(9):2658–2663.

Ramage, D., Manning, C. D., and McFarland, D. A. (2010). Which universities lead and lag? toward university rankings based on scholarly output. In *Proc. of NIPS Workshop on Computational Social Science and the Wisdom of the Crowds*. Citeseer.

Ramage, D., Rosen, E., Chuang, J., Manning, C. D., and McFarland, D. A. (2009). Topic modeling for the social sciences. In *NIPS 2009 Workshop on Applications for Topic Models: Text and Beyond*, volume 5.

Řehůřek, R. and Sojka, P. (2011). Gensim—statistical semantics in python.

Rizzo, G. and Troncy, R. (2011). Nerd: evaluating named entity recognition tools in the web of data. In *Workshop on Web Scale Knowledge Extraction (WEKEX'11)*.

Schilling, M. A. (2000). Toward a general modular systems theory and its application to interfirm product modularity. *Academy of Management Review*.

Schumpeter, J. A. (1942). *Capitalism, Socialism and Democracy*. Harper, New York.

Simon, H. A. (1969). *The Sciences of the Artificial*. MIT Press.

Trappeniers, L., Feki, M. A., Kawsar, F., Boussard, M., and Trappeniers, L. (2013). The internet of things: The next technological revolution. *Computer*, 46(2):0024–25.

Verspagen, B. (2007). Mapping technological trajectories as patent citation networks: A study on the history of fuel cell research. *Advances in Complex Systems*, 10(01):93–115.

von Wartburg, I., Teichert, T., and Rost, K. (2005). Inventive progress measured by multi-stage patent citation analysis. *Research Policy*, 34(10):1591–1607.

Wagner, C. and Leydesdorff, L. (2005). Network structure, self-organization, and the growth of international collaboration in science. *Research policy*, 34(10):1608–1618.

Appendix

Table E.3: Overview over the "expert" Twitter-accounts that were used for the text extraction

Twitter-id	Name	Location	Description
121684992	CATHERINE COSTE	Genomic Entertainment	MIT certificate in Genomics. Genomic & Precision Medicine UCSF. Blog: Ethics, Health & Death 2.0 - DTC Genomics
16870421	SingularityU	NASA Moffett Field, CA	Silicon Valley's leading experts on exponential technology. Follow @singularityhub @singularitylabs @suglobal @exponentialmed
6044272	Ramez Naam	Seattle	Author: Nexus / Crux / More Than Human / The Infinite Resource. Formerly a computer scientist at Microsoft. Interested in everything.
18705065	Humanity+	Global	Humanity+ is dedicated to promoting understanding, interest and participation in fields of emerging innovation that can radically benefit the human condition.
95661007	Kyle Munkittrick	Denver, NYC, San Fran	Bioethics: the unholy union of science, medicine, and philosophy. Blame no one but myself for what you find here.
16352993	Heather Knight		CMU Roboticist with a soft spot for interactive art & live robot performance: Founder @MarilynMonrobot, Director @robotfilmfest, Robo-Tech @RobotCombatSyFy!
28132585	Aaron Saenz		Writer for Singularity Hub, former Physics dude, Improv Comedian, Nomad
2443051	attilacsordas	Cambridge, UK	bioinformatician, EBI, regular Hadoop & R tinkerer, personal proteomics instigator, ex mitochondrial-stem cell biologist driven by healthy lifespan extension
15249166	Singularity Hub	NASA Moffett Field, CA	News network covering science, technology & the future of humanity. Follow @singularityu | Become HUB Member: http://t.co/wXGCjvICbk
16838443	KurzweilAINews	California/Mass	KurzweilAI (http://t.co/KD0Hq6D66p) is a newsletter/blog covering nano-bio-info-cogno-cosmic breakthroughs in accelerating intelligence
7445642	Chris Grayson	New York City / San Francisco	#Wearables / Advisor: http://t.co/ks23gJj30J / Prior ECD: http://t.co/Q4pSuEbFs4 / Events: http://t.co/bqLtGO3G5o & http://t.co/GrmHeG38Ir
16934772	tristanhambling	New Zealand	Tracking future, tech, nano, bio, neuro, info stuff, and anything new that scans past my event horizon. http://t.co/7aJFwAjkv7 also @futureseek
19004791	David Wood		Chair of London Futurists. Writer & consultant. PDA/smartphone pioneer. Symbian co-founder. Formerly at Psion and Accenture. Collaborative Transhumanist
15410587	Rod Furlan	Vancouver, BC	Artificial intelligence researcher, quant, Singularity University alum, Google Glass Explorer, serial autodidact, science lover & soon-to-be-robot
23115743	h+ Magazine	USA	h+ Magazine covers technological, scientific, and cultural trends that are changing human beings in fundamental ways.
743913	David Orban	New York, NY	CEO, Dotsub / Advisor & Faculty, Singularity University – Analyzing and applying cycles of accelerating technological change. Flowing in wonderment.
19748200	Gizmag		I am a website about emerging technologies.
19722699	Popular Science	New York	Science and technology news from the future! Tweets from @RosePastore
138222776	Neurotechfuture	Boston, MA, USA	The future of life, humanity, and intelligence rests in the minds and hands of the innovators who envision, guide, and build it.
594718367	Grishin Robotics	New York	Everything about consumer robotics, connected devices & IoT. Published by the first robotics investment company. Founder - @dgrishin, feed editor - @Valery_Ka.
86626845	Eric Topol	La Jolla, CA	Cardiologist, geneticist, digital medicine aficionado, Editor-in-Chief, Medscape, author of The Creative Destruction of Medicine
15808647	MIT Tech Review	Cambridge, MA	We identify important new technologies — deciphering their practical impact and revealing how they will change our lives.
101775759	Hizook.com	San Jose, USA	Robotics News for Academics & Professionals by Travis Deyle
44910688	Robot Magazine	Ridgefield, CT USA	The latest in hobby, science and consumer robotics.
16695266	ChiefRobot	Boston	Your daily dose of robots.
151648741	RobotoWear		Clothing for humans, inspired by robots. Robot t-shirts, hats, polos and hoodies.
87468736	Eric Tatro	Chicago, IL	Tweets about transhumanism, the singularity, AI, nanotech, biotech, robotics, life extension and human enhancement. All tweets and opinions are my own.
103516873	Willow Garage	Menlo Park, CA	Helping to revolutionize the world of personal robotics
6778032	Robert Oschler	Idaho	Artificial Intelligence and smart phone developer, currently focusing on speech recognition and natural language understanding applications and robotics.
18066713	robots_forever	Tokyo, Japan	Robot news, robotics research, combat and humanoid robot events, and other robot coverage from Japan.
8125922	Alexander Kruel	Germany	Transhumanist, atheist, vegetarian interested in math, programming, science fiction, science, language, philosophy, consciousness, the nature of reality...
22910080	Rob Spence Eyeborg	Toronto, Canada	We've built a wireless video camera eye. Tweets about privacy, cyborgs, prosthetics, eyepatches, Star Trek, The Bionic Man, and Augmented Reality.
7796912	Transhumanists	New York, NY	Singularity, Transhumanism, Artificial Intelligence, Human Enhancement, Stem Cells, Nanotechnology, Renewable Energy
15784353	Sensium		Revolutionary body monitoring for healthcare: wireless, intelligent, continuous, low-cost.
23116280	Popular Mechanics	New York City	The best in tech, science, aerospace, DIY and auto news. Customer Service: http://t.co/rYWTFWzg2R

Notes: Data extracted using the Twitter API in May 2014. Accounts can be freely accessed using https://twitter.com/intent/user?user_id=[insert here the twitter id]

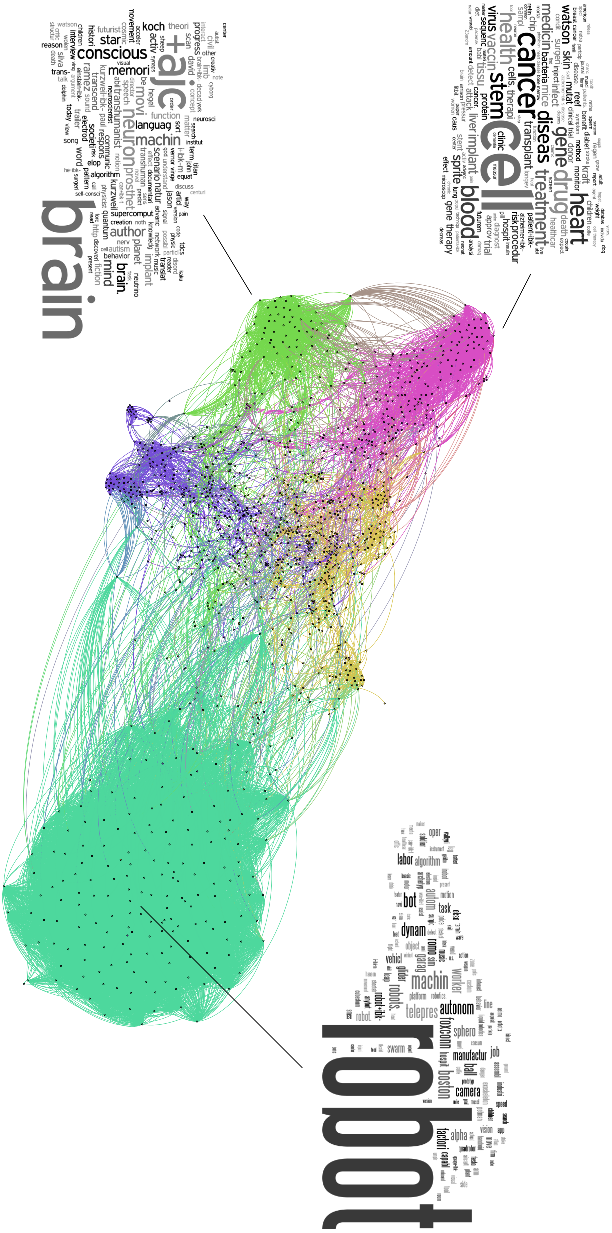


Fig. E.7: Static Community Detection: Document similarity network of the whole corpus

Table E.4: Network and community statistics over time

	2011, 2^{nd}	2012, 1^{st}	2012, 2^{nd}	2013, 1^{st}	2013, 2^{nd}
N nodes	320	293	341	163	233
N edges	3,979	2,579	3,445	1,105	1,752
N communities	74	49	66	30	36
Max. community density	0.58	0.77	0.63	0.75	0.71
Max. nodes community	54	34	28	21	26

Table E.5: Overview over top 10 Persons in the corpus

Person	Frequency	Description
Ray Kurzweil	133	Raymond "Ray" Kurzweil (born February 12, 1948) is an American author, scientist, inventor, futurist, and is a director of engineering at Google. Aside from futurology, he is involved in fields such as optical character recognition (OCR), text-to-speech synthesis, speech recognition technology, and electronic keyboard instruments.
Peter Diamandis	53	Peter H. Diamandis (born May 20, 1961) is a Greek-American engineer, physician, and entrepreneur best known for being the founder and chairman of the X PRIZE Foundation, the co-founder and chairman of Singularity University and the co-author of the New York Times bestseller Abundance: The Future Is Better Than You Think.
Peter Thiel	18	Peter Andreas Thiel (born October 11, 1967) is an American entrepreneur, venture capitalist, and hedge fund manager. Thiel cofounded PayPal with Max Levchin and served as its CEO.
Daniel Kraft	15	Daniel Kraft, M.D. is an NIH funded faculty member affiliated with Stanford.
Peter Norvig	15	Peter Norvig (born 1956) is an American computer scientist. He is a Director of Research (formerly Director of Search Quality) at Google Inc.
Jason Silva	14	Jason Silva (born February 6, 1982) is a Venezuelan-American television personality, filmmaker, and performance philosopher. He resides in Los Angeles, California and New York City.
Larry Page	13	Lawrence "Larry" Page (born March 26, 1973) is an American business magnate and computer scientist who is the co-founder of Google, alongside Sergey Brin. On April 4, 2011, Page succeeded Eric Schmidt as the chief executive officer of Google.
Steve Jobs	12	Steven Paul “Steve” Jobs (born February 24, 1955 – October 5, 2011) was an American entrepreneur, marketer, and inventor, who was the co-founder, chairman, and CEO of Apple Inc. Through Apple, he is widely recognized as a charismatic pioneer of the personal computer revolution and for his influential career in the computer and consumer electronics fields, transforming “one industry after another, from computers and smartphones to music and movies.” Jobs also co-founded and served as chief executive of Pixar Animation Studios; he became a member of the board of directors of The Walt Disney Company in 2006, when Disney acquired Pixar.
Elon Musk	8	Elon R. Musk (born June 28, 1971) is a South African-born Canadian-American business magnate, inventor and investor.

Notes: Descriptions extracted form Wikipedia

Table E.6: Overview over top 20 research facilities in the extracted corpus

Item	Frequency
singularity university	157
singularity institute	18
willow garage	14
computer history museum	13
foresight institute	12
stanford university	12
university of california	12
international space station	10
university of illinois	9
university of washington	9
washington university	8
carnegie mellon university	7
university of texas	7
duke university	6
nasa ames campus	6
national cancer institute	6
tel aviv university	6
university of michigan	6
university of pittsburgh	6
university of tokyo	6

Table E.7: Overview over top 20 companies in the extracted corpus

Firm	Frequency
google	280
singularity university	164
youtube	129
facebook	97
ibm	64
amazon	55
twitter	50
the new york times	44
microsoft	39
apple	27
irobot	25
intel	23
autodesk	22
paypal	22
wall street journal	21
bbc	19
singularity institute	19
nokia	18
techcrunch	17
cisco	16

Paper F

Technological Change and Investments on a Rugged Landscape – An Agent Based Simulation

Daniel S. Hain[†] and Elena Mas Tur[ψ]

[†] *IKE, Department of Business and Management, Aalborg University, DK*

[†] *INGENIO (CSIC-UPV), Universitat Politècnica de València, ES*

The layout has been revised, and a preface not included in the original article has been added.

Abstract

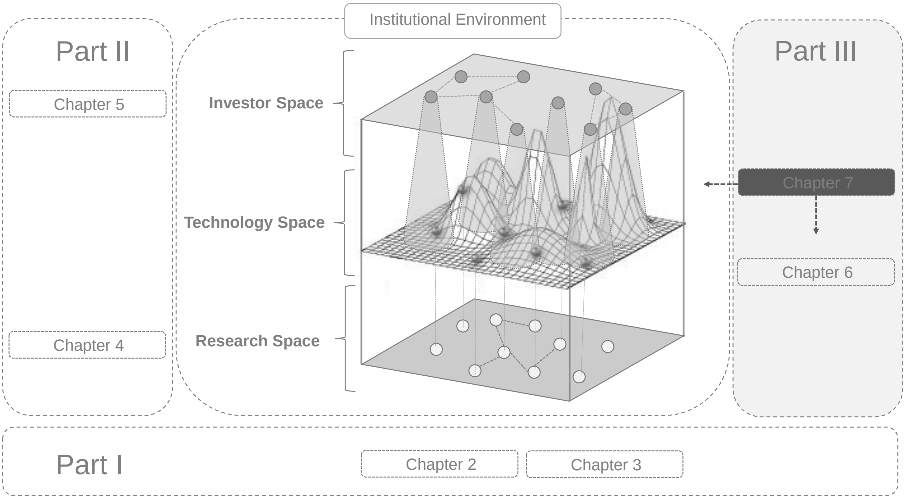
In this paper, we present an agent-based simulation model of technology investment by heterogeneous and interacting financial agents. Investment decisions are explained by the topology of the technology landscape, the agents' capability to receive and interpret incomplete landscape information, and their investment capacity. We are particularly interested in the effects of different information-sharing an co-investment network structures among agents on the rate and direction of technological change. We model these agents as to observe emerging technologies on a technology "fitness landscape", and select potential investment targets according to their perceived risk-adjusted returns, where risks are a function of the technology's maturity and the returns of the achieved technology performance. Subject to imperfect information and bounded rationality, financial agents are heterogeneous in their view of the landscape determining the potential investment targets they are able to spot, as well as in their forecasting ability determining the accuracy of their prediction of achievable technological fitness. Assuming a trade-off between search radius and forecasting ability, the population of financial agents will consist of more specialized investors with a narrow view on the landscape but high forecasting ability within this area, and more generalized ones who can search a large area but have a low forecasting ability. We observe which configuration of financial agents lead to high rates of technological change and diversity. In a next step, we introduce investor networks and allow agents to co-invest together in order to pool financial resources and get access to their forecasting capability in a specific technological domain. We compare which investor network structures and compositions lead to the high rates of technological change and diversity on a given technology landscape. Results from a Monte Carlo simulation indeed indicate networked investor population to outperform isolated investor performance, an effect that tends to increase with complexity of the technology landscape.

Preface

After the theoretical, as well as empirical groundwork, in this chapter my co-author Elena Mas Tur and I make a first attempt towards more predictive models by developing a mathematical formalization of the interaction between finance, research and technological change. In detail, I develop a model of heterogeneous and interacting financial agents, making investment allocation decisions in research projects resulting in technological change. Investment decisions are explained by the topology of the technology landscape, the technological maturity of potential investment targets, the agents' capability to receive and interpret incomplete landscape information, and their investment capacity. Thereby, I incorporate the central insights from the theoretical theoretical building elaborated in other chapters of this Ph.D. thesis. Subject to incomplete information and bounded rationality, financial agents are heterogeneous in their knowledge and information at hand to identify and assess the outcome of investments in certain technologies. To mitigate incomplete and asymmetric information, with increasing technological complexity, investors might decide to focus on a narrow technological field to accumulate relevant experience within that area. This trend of specialization on modern capital markets (Amit et al., 1998; Black and Gilson, 1998; Cressy et al., 2007)[1] leads to asymmetric information in the market for technology finance – meaning an uneven distribution of existing information and capabilities among heterogeneous investors and other relevant agents. This simple fact has two immediate theoretical implications which I stress throughout this thesis. First, it calls for explicitly considering the micro-foundation of innovation and technology investments – since investors will asses certain investments differently with respect to their perceived risks and returns. Second, it offers an explanation for the emergence of investor networks to leverage synergies among those heterogeneous agents. Yet, asymmetric information among investors also creates tensions manifesting in agency and governance issues, which I also discuss in this chapter. Complex systems theory also enters the chapter by modeling financial agents to observe emerging technologies on a technology "fitness landscape". Finally, it is well established that during the technology life cycle, some characteristics of technologies and associated industry alter tremendously (Klepper, 1997), particularly the capital intensity, risks, and returns. With considering these insights, I apply a dynamic perspective on technological change.

[1] Which among others manifests in the emergence of new forms of financial intermediaries such as venture capitalists with in depth knowledge on technologies as well as their markets.

Fig. F.1: Positioning the paper in the theoretical framework



While my main focus here lies on the effect of finance on technological change – the guiding topic of this PhD thesis, I exhaustively discuss possibilities to model interactions within and between all three considered dimensions (research, technology, and investment space). I carefully elaborate on the endogeneity between characteristics of all three dimensions, yet demonstrate that - for the sake of analytic orthogonality - they can be studied in isolation, at least in the short run. Thus, this chapter aims to link all three dimensions of technological change, but emphasizes the up to now under-researched and -conceptualized finance space.

Combining most collected insights gathered during my Ph.D. fellowship, this is the latest chapter written. It was firstly presented at the "DRUID Winter Academy" 2015 in Aalborg, and afterwards at the "DRUID Summer conference" 2015 in Rome. It is currently available as an IKE working paper.

1 Introduction

The duality between finance and technological change has long been recognized as a main driving forces behind capitalist dynamics and economic progress (Perez, 2004, 2010; Schumpeter, 1934, 1942). The search for new technologies is a risky and uncertain endeavor, especially for the ones leaving established technological trajectories and engaging in more radical forms of innovation (Dosi, 1988). Yet, in modern capitalistic economies, not only researchers, inventors and entrepreneurs, but also their providers of capital share this risk. Without an investor able and willing to financially back such endeavors, ideas remain ideas and will not enter the commercial landscape as new products, services, or processes. Consequently, understanding investors decision processes under uncertainty becomes integral to explain technological change.

A long tradition of research dating back to the seminal contributions by Arrow (1962) and Nelson (1959)indicates investments in innovation to be particularly difficult for investors to handle. One of the main arguments put forward lies in the nature of information required to assess their profitability. For mature technologies embedded in a likewise stable and well understood technological system one can apply traditional risk-adjusted return projection techniques. Here, the expected profitability of an investment is quantified by summing over a set of possible outcome-scenarios weighted by their probability. In case of emerging technologies diverting from established trajectories, the still unfolding set of information on single technologies as well as their interaction in a technological system leads to "true uncertainty" (Knight, 1921), preventing accurate predictions of timing, technological features, and economic consequences of innovations along these lines. This prediction problem tends to amplify with increasing interdependence and associated complexity of modern technological systems, where the performance of any single component is highly sensitive on changes in other parts (Fleming and Sorenson, 2001; Kauffman and Macready, 1995).

Confronted with incomplete information and limited capabilities to process them, investors acting under "bounded rationality" (Simon, 1955) to a large extent rely on simple heuristics, rules-of-thumb and intuition when assessing potential investments (Tversky and Kahneman, 1974). To mitigate information deficits and improve applied heuristics, investors can focus on a narrow set of investments to accumulate relevant experience within that area. This trend of specialization in modern capital markets (Amit et al., 1998; Black and Gilson, 1998; Cressy et al., 2007) causes asymmetric information in the market for technology finance, meaning an uneven distribution of existing information and capabilities among investors and other relevant agents.

A way to mitigate information deficits outside one's own area of expertise is to mobilize knowledge and capabilities of partners within an investor's network of informants (Casamatta and Haritchabalet, 2007; Fiet, 1995). In addition, for equity based technology investments, it is also common practice to team up with other investors and co-invest together (also referred to as "syndiation") in the same target. In such co-investment networks, investors can pool capabilities and financial resources (Ferrary, 2010) in order to achieve superior investment performance (Hochberg et al., 2007). A long tradition of social science research ranging from seminal work by Simmel (1955) to Merton (1957), Granovetter (1973), Burt (1992) to recent work, provides sound evidence as to how the behavior of individuals and organizations is strongly affected by the way they relate to and interact with larger collectives. Consequently, the topology of such investor networks is also said to strongly affect the amount of investments, their pattern and performance on the investor – as well s system-level (Baum et al., 2003).

Indeed, we can draw from a large body of literature providing theoretical frameworks as well as empirical evidence, as to how certain designs of financial systems (Beck and Levine, 2002; Dosi, 1990; Rajan and Zingales, 2001), types of investors (Kortum and Lerner, 1998, 2000), and their network structure (Baum et al., 2003; Hochberg et al., 2007) impact the amount and performance of investments in emerging technologies. Yet, from a static perspective it is not obvious how conducive such investments are for technological change. To reach the market and have meaningful economic and social impact, technologies have to attract investors in every development stage, from the lab to the scaling up for mass market production. Mismatches between technology characteristics with the capabilities and rationales of the investor population can cause investment bottlenecks (commonly refereed to as financial "valleys of death", where technologies "die" due to underinvestment) and seriously jeopardize further progress. During the development of a technology along its' life-cycle, many of its' characteristics relevant for investors tend to alter substantially (Klepper, 1997; Nelson, 1994; Utterback, 1994). Most relevant, the accumulation of available knowledge regarding the general feasibility and interaction with other components of the system de-risks technology, decreasing the chance of failure and making further progress more predictable (Dosi, 1988). At the same time, technology development tends to become more capital intense in later stages close to commercialization. While maturing, technologies may also gradually alter their own logic in terms of how they function and on what kind of problem of which they can be applied. Consequently, the same technology will appeal to a different set of specialized investors in different stages of its life-cycle, thus without the right mix of such investors present, this technology will be unlikely to reach the market. Information sharing and co-investment networks here have the potential to mitigate the negative effects of lacking capabilities and resources of particular investors, depending on their structure.

In this paper, we present an agent-based simulation model of technology investment by heterogeneous and interacting financial agents. Investment decisions are explained by the topology of the technology landscape, the agents' capability to receive and interpret incomplete landscape information, and their investment capacity. We are particularly interested in the effects of different information-sharing an co-investment network structures among financial agents on the rate and direction of technological change. We model financial agents to observe emerging technologies on a technology "fitness landscape", and select potential investment targets according to their perceived risk-adjusted returns, where risks are a function of the technology's maturity and the returns of the achieved technological performance.

Subject to imperfect information and bounded rationality, financial agents are heterogeneous in their view of the landscape determining the potential investment targets they are able to spot as well as in their forecasting ability determining the accuracy of their prediction of achievable technological fitness. Assuming a trade-off between search radius and forecasting ability, the population of financial agents will consist of more specialized investors with a narrow view on the landscape but high forecasting ability within this area, and more generalized ones who can search a large area but have a low forecasting ability. We observe which configuration of financial agents lead to high rates of technological change and diversity, and in which technologies get stuck in the "valley of death". In a next step, we introduce investor networks and allow financial agents to co-invest together with their connected peers in order to pool financial resources and get access to their forecasting capability in a specific technological domain. While we expect such networks *per se* to be conductive, we are interested which network structures and compositions lead to the high rates of technological change and diversity. Therefore, we compare the results of more homogeneous or heterogeneous networks in term of the agents technological knowledge and degree of specialization.

Results from a Monte Carlo simulation on different investor network structures and technology landscape complexity indeed indicate networked investor population to outperform isolated investor performance, a effect that tends to increase with complexity of the technology landscape.

Our general attempt is to provide a more nuanced understanding of the interplay between technology characteristics and decision making processes of bounded rational investors and emerging characteristics of a technological system. We thereby contribute to literature on technological change as well as financial and investment theory by establishing an analytical link between them. We are also convinced that this model provides a solid basis for simulations to be done, enabling them to derive important implications for theory and practice. For policy making, it provides the potential to analyze real life investor populations and, based on the results facilitating technological change, by policies aiming to reconfigure investor network structures or by targeted public funding in problem areas.

The remainder of the paper is structured as followed. Grounded on prior work which we review briefly, in section 2 we present a conceptual model of investments on a technology landscape by connected heterogeneous financial agents, and in section **??** its mathematical formalization. Section **??** summarizes preliminary results from a Monte Carlo simulation on different investor network structures and technology landscape complexity. Finally, in section 5 we conclude, provide implications for theory and practice, and fruitful avenues for further research.

2 Conceptual Framework

In neoclassical economic theory, technological change is commonly envisioned as an equilibrium shifting exogenous shock, or as something subject to a production function with a determined relationship between inputs such as R&D spending, and outputs such as patents or sales with new products. A more modern understanding depicts technological change inherently as happening endogenously to the system it is embedded in, where the system's components are interdependent among each other as well as with elements outside the system's boundaries (Freeman, 1987; Lundvall, 1992; Nelson, 1993). In the same vein, innovation which is believed to be a driving force of technological change, is above all a social process not happening in isolation but nurtured by the collective interaction of various directly involved agents, as well as supporting ones (Powell et al., 1996).

Investors and other provides of external finance are among those crucial supporting agents. Indeed, without the commitment of financial resources, ideas remain ideas, independent of their potential. Depending on the capital intensity of the technology, one can develop ideas and invention with a minimum commitment, as is the case with classical garage inventions. However, this can only go so far, since a fair share of progress is usually achieved by the testing of such inventions in real life situations, where technological and economic properties can be gradually improved. Through their decision of whom to provide capital and to whom not, financial institutions such as banks and stock markets nowadays represent the major ex-ante selection device every innovating firm and project has to face. Thus, with their allocation of resources, they play a major role in determining the amount of innovative effort, as well as its trajectory (Dosi, 1990).

This pivotal role of finance in facilitating innovation and propelling technological change is already emphasized in the work of Schumpeter (1934, 1942), who claims innovations by a creative entrepreneur based on credit creation by a risk-taking banker as the force behind capitalist dynamics. The entrepreneur-banker duality here has to be considered as a symbiotic relationship: the entrepreneur creates potential high-return investment opportunities for the banker, who in turn enables venturing possibilities for the entrepreneur by providing external finance.

However, it is well understood that this powerful, yet simple, relationship does not capture the full complexity of the financial system and the multitude of heterogeneous involved actors influencing the allocation of resources towards innovative activity. Research during the last decades has provided a more nuanced understanding as to how the design of financial systems (Beck and Levine, 2002; Dosi, 1990; Rajan and Zingales, 2001), the behavior of investors on financial markets (Perez, 2002, 2004, 2010), public funding (Mazzucato, 2011), and firm level resource allocation (Tylecote, 2007) influence the rate and direction of technological change.

In the following, we will elaborate on what we believe to be a crucial yet underexplored determinant of technological change: How the composition of investors with heterogeneous resource endowments impacts investment patterns in technologies with certain characteristics, and how this is mediated by information-sharing and co-investment networks. Before clarifying the mechanics and other mathematical details of the simulation model, we will proceed with placing this link between investor characteristics, networks, and resulting investments in technological change in a bigger context. We do so by first elaborating on the dynamics between three main dimensions of technological change, namely (i.) the research space where technology is developed by research agents, (ii.) the financial space where financial agents allocate investments among the innovation projects developed in the research space, and an intermediate (iii.) technology space in which research operates and investors evaluate.

2.1 The Dimensions of Technological Change

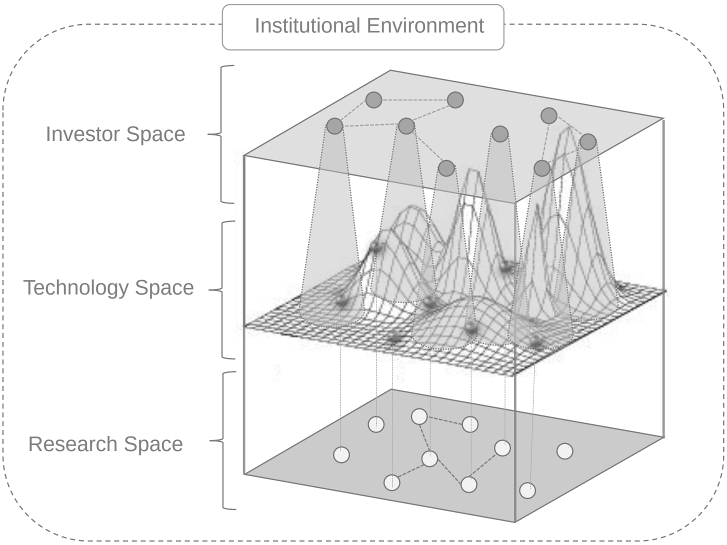
Following Schumpeter's conceptualization of the entrepreneur-banker (and broader, finance and economic progress) duality, we envision technological change primarily as the outcome of micro-level activities between (i.) agents developing invention by conducting research and development, and financial agents providing the capital to do so (ii.). Yet, in line with his neo-schumpeterian heritage (eg. Hanusch and Pyka, 2007a; Winter, 2006) we see this relationship to be embedded in a more complex context, and the resulting innovation as the outcome of interactions between various subsystems (Carlsson and Jacobsson, 1997; Lundvall, 1992; Malerba, 2002; Nelson, 1993) and embedded heterogeneous economic agents (Hanusch and Pyka, 2007b; Pyka, 2002).

As a basic framework for our model explaining technology investments and their impact, we consider three dimensions of technological change[2]: (i.) the research space where technology is developed by research agents, (ii.) the intermediate technology space which takes the form of a fitness landscape representing potential performance of certain technology configurations, and (iii.) the financial space where financial agents search for possible investment opportunities in technology space. In detail, we aim to explain investment decisions of heterogeneous financial agents with incomplete information regarding investment opportunities as well as their technological potential. Further, we elaborate on possible mediating effects of information-sharing and co-investment networks among financial agents. The outcome of such search and investment processes - technological change - manifests in a realized reconfiguration of components in a complex technological system consisting of interrelated components. We know that technological systems are always embedded in - and co-evolve with - a social and institutional context (Bijker et al., 1987; Hughes, 1987). This is illustrated in figure **??**. Here we see research, as well as financial space, to be populated by respective agents

[2]For a more exhaustive discussion on these dimensions, their theoretical foundation and interplay, consider Hain (imeo)

- investors and researchers - which are connected by certain cooperation pattern.

Fig. F.2: Linking Investment and Research on the Technology Landscape



In brief, research agents generate potential innovation projects that trigger technological change if they attract investments by financial agents, while both research and investment activities are constrained by the corresponding agents insight in the landscape. In the following, we shall elaborate in detail about the intuition, theory, and mechanisms behind this processes. In the model to be presented in this paper, we are interested in the effects of investor characteristics and networks on investment pattern resulting in technological change. We here assume the technology landscape, as well as investment opportunities to be given exogeneous. While in reality for sure multiple feedback between finance and research activities, for the sake of simplicity we here assume them to be analytically orthogonal at least in the short-term.[3]

2.2 The Agents involved in Technological Change

As outlined before, both research as well as financial space are populated by heterogeneous agents. Our main interest, financial agents, are to be understood as various kinds of entities who actively invest in technological change,

[3]However, in later sections we discuss possible extensions, including feedback loops between investor and research activities and networks.

meaning they are willing to financially back firms and products or projects aiming to alter or improve a certain technology. This can be classical institutional investors such as pension funds, private equity (PE), venture capital (VC) investors, and other financial institutions such as banks which operate under the following assumptions. (i.) Their main rationale is to optimize the perceived risk-adjusted returns of their investments. (ii.) Their returns depend on and scale with the performance of the technology under investment. This is usually the case in equity based investments.[4]

Research agents can be all kinds of actors actively participating in the search for technological advancements, inventors, and entrepreneurs so to say. The main assumption here is that they are in need of external finance to do so. This holds true for most private and academic inventors, other non-public and also public research institutions, private sector SMEs as well as larger companies. Nevertheless, we obviously exclude a fair share of technological progress happening in large firms that are able to fully finance their research endeavors internally with means of accumulated profit. In this model, we treat activity in research space as a black-box and assume the behavior of research agents as given, where only their output in terms of exogenous proposed innovation projects searching for finance enters.

2.3 Investments and the Technology Life-Cycle

It is well established that during the technology life cycle, some characteristics of technologies and associated industry alter tremendously (Klepper, 1997). Particularly, two of those characteristics are said to alter how it might appeal to certain types of financial agents. First, technologies in early stages of the life cycle, without established technological trajectories to guide the direction of search, are commonly associated with higher risks, and innovation projects in such technologies show a higher probability of failure (Dosi, 1982, 1988; Freeman et al., 1983). Second, capital requirements for further technology development and deployment tend to increase while a technology moves from the lab to the market. To gain legitimacy and ease the way to commercialization, it often is necessary to demonstrate the feasibility and functionality of the invention in a real-life setting of appropriate scale. Finally, to become an innovation, an invention has to be introduced to the commercial market, with all the costs associated.

[4]Later, we discuss how to relax this assumptions, and allow for diverging rationales (eg. governments who might aim to increase technological progress rather the return of their investments) and pay-offs (eg. dept based finance, which always offers a ex-ante fixed percentage of the investment as return in case of success, and default in case of failure).

This perspective on technology development – including different types of agents, investments, and investors – offers valuable insights. Mismatches between innovation projects proposed by research agents, technology characteristics, and financial agents capabilities can cause financial bottlenecks at any of these stages and seriously jeopardize the further technology development. Such bottlenecks are commonly referred to as "valleys of death" in which technologies "die" due to underinvestment. Such valleys of death are particularly likely to occur in the post-lab but pre-market stages. Moving them from the lab to a full scale demonstration project can get very capital intense technologies, and public funding – which often funds early research gets scarcer at this stage. When this challenge is managed, scaling up for full commercialization becomes the next challenge – when they get capital requirements get to high for early stage investors but the technology risk is still unacceptably high for most institutional investors with suitable capacity.

2.4 Search on the Technology Landscape

Before being able to discuss investment decisions in the development of novel technologies, we are in need of a framework which defines the mechanisms on how the search for technology development is conducted, and provides metrics for the rate and direction of technological progress and its profitability for investors.

The concept of "fitness landscapes" has proven useful to map and analyze selection processes as stochastic combinatory optimization in complex systems; in this case, how technological change by the way technologies within a larger technological systems are related to each others. In its core, such a landscape represents a multidimensional mapping of components with attributed states of solution parameters to some measure of performance representing an elements fitness (Kauffman, 1993). In this fitness dimension, the landscape shows high performance "peaks" as well as low performance "valleys", where the peaks can be understood as the "evolutionary frontier" – the highest reachable level of a certain evolutionary path with respect to relevant environmental conditions. In the classical model proposed by Kauffman (1993), biological evolution of complex organisms, in which the functioning of genes is interdependent, has been analyzed as "hill-climbing" activity on NK fitness landscapes through random mutation and natural selection. Since the components are epistatically related, their fitness depends not only on their own states but also the "interaction" with their neighbors. The systems complexity is determined by the number of its components and their degree of epistasis, and manifests in the "ruggedness" of the landscape (Levinthal, 1997). Simple systems, with a small set of components and/or low epistatic relations among them, correspond to smooth landscapes with a few evenly distributed peaks, whereas a complex ones corresponds to a landscape with many unevenly distributed peaks of varying height. A main insight derived from such models is the efficiency of different evolutionary processes. With increasing complexity and associated ruggedness of the landscape, it becomes more and more unlikely that pure local selection will lead to globally optimal outcomes, but rather to a lock-in into locally optimal *evolutionary pockets*.

This evolutionary metaphor has also been adopted to mimic research strategies of firms, concluding that with increasing complexity of the technological/scientific paradigm one is operating in, the more important become exploration oriented research strategies in contrast to local incremental exploitation of already existing solutions (March, 1991). It is further highlighted that increasing interdependence between technologies makes it very hard to integrate them in existing systems (Fleming and Sorenson, 2001). Indeed, modern technological systems appear to develop towards increasing epistasis, making outcomes of re-combinatory processes such as R&D activities harder to predict. In order to understand innovation activity in many technological fields, it thus becomes important to understand the dynamics of these recombination which happen on large scale and with increasing pace. In the current energy system, for instance, the successful development of potential new energy sources is highly dependent on how their characteristics such as their load fluctuation profiles interact with existing energy production, transmission, and storage infrastructure. Consequently, the *ex-ante* prediction of research outcome in this area appears to be impossible without immense technological knowledge, a fact that daunts many financial agents to invest in emerging renewable energy technologies (Kenney, 2011).

2.5 Investments in Technological Change

In line with Schumpeter's entrepreneur-banker duality, attempts to search for technological improvement conducted by research agents can only be realized if able to attract an investment by a financial agent (ii.). In other words, one can envision financial agents to "unlock" potential inventions to be transformed to innovations in technology space. To make such an investment happen, three necessary conditions have to be fulfilled.

First, the financial agent has to be aware of the investment opportunity offered by the innovation project. Assuming the market for technology investments to be imperfect and necessary information often private and opaque, this will not always be the case but rather depend on the outcome of active search of financing agents for investment opportunities, or by researching agents for investors. The radius of this search will obviously face some constraints, which could be geographical, cultural, institutional, or technological, where we in the ongoing focus on the latter. We assume investors depending on their competence profile and investment history to be closer related to particular (more or less narrow) technologies, where insider knowledge and contacts eases the search for investment opportunities. In the same way, financial agents operating in a certain area of the technology space enjoying higher visibility and probably status among research agents, are thus more likely to be approached by them for funding. As illustration, one can imagine investors to observe the technology landscape with a birds-eye perspective as in figure **??**.

Second, the financial agent has to be sufficiently endowed with capital required by the project. This investment capacity greatly varies among financial agents. While investors such as business angels, who fund their activity with private wealth, tend to be rather constraint in the amount of capital they can mobilize, large investments banks often easily stem multi-billion deals.

Third, the financial agent has to assess the investment as potentially profitable. Generally, it is well understood in investment theory that the primary rational of financial agents' investment allocation is to maximize their risk adjusted rate of return from their capital under management. This is traditionally done by summing the profits of possible outcome scenarios weighted by their profitability, in the simplest form as stylized in equation F.1:

$$\Pi_i(\pi_i, \varphi_i) = \sum_{i=1}^{n} \frac{\pi_i \varphi_i}{N} \tag{F.1}$$

where π_i is the expected rate of return (which can be positive or negative) achieved in scenario i, and φ_i its probability. In case of a symmetric unimodal distribution of outcomes, the average rate of return is to be found at the probability density function's maximum ($\varphi_i'(\pi_i) = 0$). Obviously, fat tails on the left (loss) side of the distribution associated with higher risks of the investment also require equally high weights on the right (gain) side to maintain a certain average rate of return.[5] When assuming financial agents *per se* to

[5]This is true for equity based investments, where the investors equally participate in losses as well as benefits. For debt based finance of innovation projects, only the left tail of the distribution

be risk averse, for equal average rates of return they prefer investments with lower variance in outcome (Arrow, 1965; Pratt, 1964).[6]

Most of the discussion up to now conceptualizes modern financial intermediaries as Schumpeter's "reckless bankers", willing to risk it all in prospect of potential extraordinary gains. In contrast, traditional investors such as commercial banks are said to be risk averse and thus more prone to invest in mature technologies not subject to the "liability of newness". With changing the typical firm populations characteristics during the technology and industry life-cycle, this goes hand in hand with a natural separation of firms that receive such investments; entrepreneurial start-ups, in the case of early stage investors, and established SME's and MNE's in the case of late stage investors. Again, the main mechanisms that create this separation are idiosyncratic risk preferences among financial agents. We, however, propose a different mechanism attained by disentangling (systemic) risk and uncertainty components of investments.

$$\Pi_i(\pi_i, \varphi_i) = \sum_{i=1}^{n} \frac{\pi_i \varphi_i}{N}(1 - var(\pi_i)\alpha^k) \tag{F.2}$$

where α^k would represent the risk preferences of financial agent k. The heterogeneity of this parameter leads to a separation of investors in Schumpeterian risk-takers such as business angels or venture capitalists investing in emerging technologies, and traditional risk-avoiding investors such as banks investing in mature technologies in late stages of their life-cycle. By disentangling risk and uncertainty components of investments, we suggest a different mechanism to be at work. While we assume the risk of an investment to be objectively measurable by all financial agents, its uncertainty is based on a subjective evaluation under bounded rationality, thus heterogeneous among investors (Knight, 1921). In contrast to risk, uncertainty implies that neither the probability of different outcome states, nor the characteristics of this states can be *ex-ante* quantified. For investments in emerging technologies, we attribute this inability primarily to the financial agent's incomplete information regarding the technology's characteristics and interaction with other elements of the present technological system.

Financial agents involved in investment decisions under uncertainty basically can react in two ways. They might specialize on investments in a lim-

matters, since investors participate in partial or total default of the loan but the returns are truncated by the *ex-ante* agreed interest rate in case of success. Therefore, the mostly fixed interest rate has to capture all potential losses.

[6]Which holds on average in most settings, yet some situation and personal characteristics might lead to an active "risk taking" behavior (Tversky and Kahneman, 1992).

ited set of well-understood technologies to accumulate specific information improving their ability to forecast future developments and thereby identify investments with possible abnormal profits. Consequently, an informed investor able to identify future profitable development scenarios will be more likely to undertake objectively risky investments in emerging technologies than others. As an alternative to decreasing the uncertainty of particular technologies, financial agents might also decrease the overall risk/uncertainty of their investment portfolio by cross-sectional diversification across technologies (King and Levine, 1993). Obviously, broadly diversified financial agents investing in various technologies have little opportunities to accumulate technology-specific knowledge and thereby increase their forecasting ability. Without an insight of the technology's potential upsides, such investors' risk-return evaluation will therefore naturally be more sensitive to generic risks associated with emerging technologies "liability of newness" and favor technologically mature alternatives. To sum up, we suggest the decision to invest in more risky emerging technologies to be a function of the investor specific forecasting ability rather than explicit or implicit risk preferences. We here assume a trade-off between depth and breadth of search. Agents able to invest in a broad set of different technologies will suffer from limited forecasting capabilities, and *vice versa*.

In addition to internally accumulating technological knowledge, financial agents also use their network to access external information of their cooperation partners. However, establishing and maintaining relationships to other agents usually comes with a cost, so agents will not indefinitely expand their network beyond a certain beneficial size to get access to even more information. Furthermore, when information is distributed asymmetrically between agents, the less informed ones have to find ways to verify the credibility of signals received from their supposedly better informed peers. When discussing the assumed trade-off between broad access to external information and its verification, arguments of particular network structures are often brought forward – in particular the benefits of brokerage versus closure. In essence, it is argued that brokering a relation between actors that would otherwise be unconnected, also refereed to as structural holes, provides information advantages in terms of access to a diverse set of novel information (Burt, 1992, 2001). In contrast, being embedded in closed – rather than brokered – network structures facilitates the exchange of in-depth information through frequent, trust-based interactions among interconnected actors (Uzzi, 1996, 1997). Another stream of research focuses on the characteristics agents in a network rather than its structure, arguing that belonging to a network of rather homogeneous agents provides access to in-depth, specialist information, whereas being embedded in networks of rather heterogeneous agents is a source to diverse information (Fleming et al., 2007; Reagans and McEvily, 2003). We aim to contribute to the latter discussion. While we generally expect a positive effect of networking *vis-à-vis* agents investing in isolation, we investigate which distribution of actor characteristics within this networks - more homogeneous or heterogeneous - is more conducive for technological change.

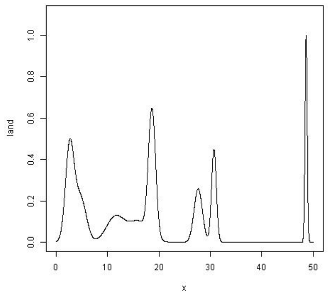
We consider three relevant characteristics of financial agents, (i.) their position in the technology landscape reflecting the core of their knowledge base, (ii.) their degree of specialization and the resulting search radius and forecasting ability, and (iii.) their capital endowment determining their investment capacity.

3 The Model

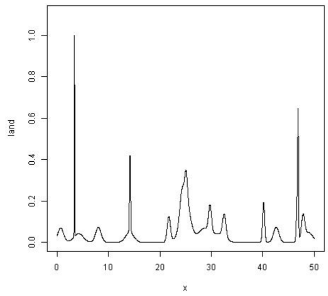
3.1 Landscape and initial conditions

First, we create a one-dimensional fitness landscape representing the space of a technological system, where different technology configurations are ordered according to their relatedness on the x-axis, and the particular configuration's fitness ($f(x), x \in \mathbb{R}$) on the y-axis. Due to this ordering of technologies, we assume the associated fitness to be a continuous function with several local minima representing low performance valleys and maxima representing high performance peaks. A fitness landscape is appropiately described by a Gaussian mixture, that is to say, a density function of a random variable obtained as a weighted sum of several Gaussian distributions with different means and different standard deviations. The number of distributions in the mixture is not equivalent to the number of peaks, but a mixture of a high number of distributions will result in a rugged landscape, while a mixture of few distributions will give a flatter, less complex landscape, as illustrated in figure F.3.

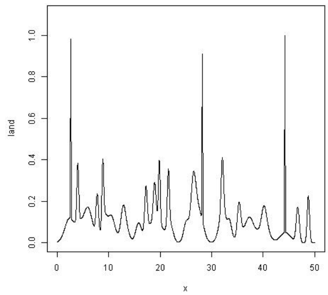
Technological progress here is associated with improving technology configurations in order to increase a technology's current fitness level. The distance from a local minimum towards the closest local optimum can be envisioned as a certain technological trajectory, and the process of gradual improvement over time towards this optimum as a technology's life-cycle. Consequently, at a local optimum a technology has reached full maturity and



(a) 10 Gaussian Mixtures



(b) 25 Gaussian Mixtures



(c) 50 Gaussian Mixtures

Fig. F.3: Different technology landscapes with 10, 25, 50 Gaussian Mixtures

exhausted its trajectory, leaving no potential for further innovation.[7] Note that the same local peak can be discovered from two directions, where the corresponding local valleys can have different heights in the landscape. This is an intuitive feature, as two different trajectories can lead to the same final technology configuration (peak), although one in a more efficient way from a better starting point.

When research agents (which could be firms, research groups, or individuals) attempt to improve certain technologies, this attempt appears as a potential innovation project k on the landscape. Its position x_k represents the

[7] While a technology life-cycle is usually linked to an industry life-cycle, it is not necessarily synchronized. Thus, even when a technological trajectory becomes exhausted, industries can still progress by altering their logic in terms what and how they produce it. However, therefore they have to enter new technological trajectories. Further, an exhaustive technology can still be commercially viable and attract investments in its deployment. It, however, does not leave room for further technological improvement.

project's initial technological configuration as basis for the further search for improvement. Together, the potential innovation projects form the choiceset χ which includes all possible technology investment in a certain technological system. For the sake of simplicity, we assume analytic orthogonality of agents' behavior in research space, the amount and position of innovation projects in χ is given exogenous.

The population of financial agents i are also positioned on the fitness landscape. Here, p_i, represents their locus of technological expertise. To cope with various issues of incomplete and asymmetric information – as well as limited forecasting capabilities – investors tend to specialize on investments in certain technologies, industries, investment types or stages, geographical regions *et cetera*. Consequently their own search strategy, visibility among potential investment targets and their networks, tends to concentrate along this specialization. The degree of specialization is determined by their search radius r_i. Low r_i indicate a very narrow specialization on certain technology investments, and high r_i a more broad and diversified investment activity. Related to this search radius, the forecasting ability h_i determines the financial agent's capabilities of predicting the further development of technologies. A financial agent with a high forecasting ability will be able to see the local peaks of a technology's trajectory, while one with a low forecasting ability will likely see only a small section of the technology's way to the peak. We assume a trade-off between forecasting ability and search radius in a way that agents with high search radius act as generalists and can spot potential investments in technologies in a broad area of the landscape, but have very limited insight in its nature and thus future development. Technology specialists on the other hand, invest only in a small area of the landscape but have a deeper understanding and more high quality information, hence can accurately predict the technology's future potential. Furthermore, a financial agent will have a better understanding of technologies close to its own position in the technology space, thus the forecasting ability decreases with the distance to the potential investment.

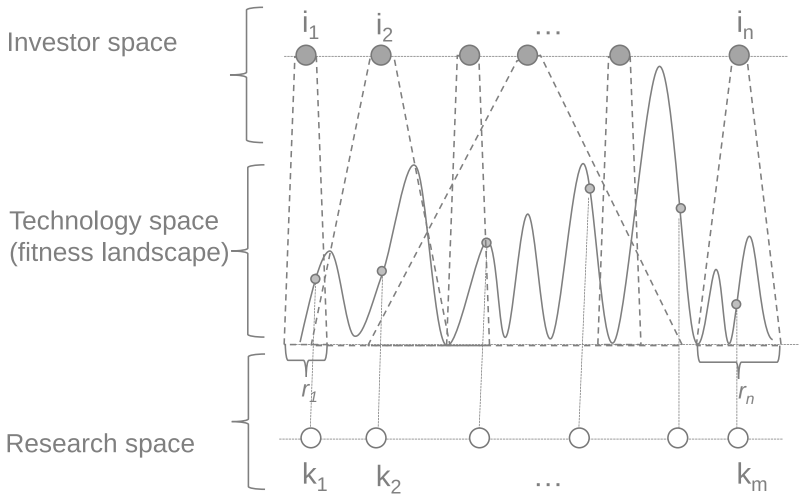
Finally, financial agents differ in their capital endowment e_i, which determines the amount they are able to invest per round in an innovation project. This endowment, proportional to the degree of specialization – as generalist financial agents tend to have – together with higher search radius and lower forecasting abilities, gives a better access to capital than technology specialists.

3.2 Investors landscape scanning

As a first necessary condition for an investment to take place, an investor has to spot an investment opportunity represented by the innovation project at all. To illustrate this process of scanning the market for potential investment targets, one can imagine investors to observe the technology landscape with a birds-eye perspective. Assuming the market for information on new technology investments to be imperfect, an investor's choice-set χ_i of potential investment targets will be limited and not contain all possible options of existing investment-ready solutions k in technology space χ. Investors may gather information on potential investments via active own search, active signals from the investment target, or referrals from their network. We here focus on the former and introduce the latter at a later point. For the moment we shall just care if the investment opportunity falls into the investor's choice-set χ_i or not, which depends on the project's position x^k, the financial agents position x_i and search radius r_i, as illustrated in figure ?? and formalized in equation F.3

$$\chi_i \subseteq \chi \quad where: \; x_i - r_i \leq x^k \leq x_i + r_i \tag{F.3}$$

Fig. F.4: Investors view on the technology landscape



3.3 Investment Decision

After a financial agent's choice set χ_i is defined, the agent evaluates the profitability of potential investments and chooses the most attractive one. We assume agents to primarily aim to maximize the risk-adjusted returns on investments (Π_i^k) by selecting among potential targets k, as stated in equation F.4:

$$\arg\max_{k \in \chi_i}[\Pi_i^k(\pi_i^k, \rho_i^k, c_i^k) = \frac{\pi_i^k(1-\rho_i^k) - c_i^k}{c_i^k} \quad where: c_i^k \leq e_i] \tag{F.4}$$

where π_i^k represents the net gains of an investment in case of success, ρ_i^k the probability of failure, and c_i^k the investments costs. The gains of such an investment (π_i^k) in reality are supposed to be a function of many variables such as product and capital market condition, project/team/firm characteristics, value added by the investor, and the technological potential of the invention. In this model we focus solely on the latter and assume the others as randomly distributed among available inventions. Hence, π_i^k only depends on the post-investment fitness of the innovation project, and the achieved increase in fitness by the investment.

The costs of an investment (c_i^k) are here approximated with the maturity of the technology, where early stage technologies are associated with low and mature technologies with high capital intensity. The cost of moving a technology from its original position x^k to a new position y^k in the technology space depends on the relative height of those positions in the technology landscape, specifically the height of the local maximum, $\overline{x}^k$, and the local minimum, $\underline{x}^k$.

$$\begin{aligned} c_i^k &= \int_{x^k}^{y^k} (\frac{x - \underline{x}^k}{\overline{x}^k - \underline{x}^k})^2 dx \\ &= \frac{f(y^k) - f(\underline{x}^k))^3 - (f(x^k) - f(\underline{x}^k))^3}{3 * (f(\overline{x}^k) - f(\underline{x}^k))^2} \end{aligned} \tag{F.5}$$

The costs representing the amount a financial agent is capable and willing to invest - and related, the gains depending on the size of the investment - in an innovation project are limited by two factors. The maximum amount of the investment cannot exceed the financial agents endowment (e_i) per period.

Net gains (in case of success) increase non-linear with achieved fitness level fx_2^k and increase of fitness level $\Delta fx_{1\to2}^k$

$$Net\ gains: \pi_i^k = c_i^k * (1 + fx_2^k) * (1 + \Delta fx_{1\to2}^k) \tag{F.6}$$

Further, the investment size is also limited by the financial agent's capabilities to forecast the technology's further development. A long tradition of research on behavioral finance tells us that such an assessment is less of an objective optimization process by fully rational agents, but rather a heuristic one by agents acting under "bounded rationality" (Simon, 1955). A major argument rests on the lack of and unequal distribution of information. The innovation process is inherently characterized by uncertainty Dosi and Orsenigo (1988), making proper predictions *per se* impossible. Private information on the side of the developers of an innovation project further results in asymmetric information, leading to the principal-agent problems (Myers and Majluf, 1984; Stiglitz and Weiss, 1981). As discussed exhaustively, one strategy of financial agents to mitigate incomplete information issues is to specialize on a particular subset of investments. To capture such specialization effects, we approximate the extent of a technology's development assessable by an financial agent as in Equation F.7.

$$h_i = (r_i * |x_i - x^k|)^{-1} \tag{F.7}$$

In addition to the potential gains, investors also care about the risk associated with potential investments, a fact that is well established in finance (Hain and Christensen, 2014) literature, but somewhat neglected in literature on technological change as well as policy making (Dinica, 2006). From a financial agent's perspective, investing in innovation is related with higher risk and uncertainty (Dosi and Orsenigo, 1988) leading to a higher variance of returns. The risks investors commonly consider are related to the (i.) firm/project invested in, (ii.) policies that might influence it, (iii.) the market it sells in, and (iv.) the technology deployed. Where the first is specific to the investment, the latter are systemic. Again, we assume invention-specific variables to be randomly distributed among investments and focus on the investors evaluation of technology risk. As a simple rule, investors will require higher returns for riskier investments in order to maintain a certain level of average returns.[8] Consequently, the expected gains are weighted by their probability of success ($1 - \rho_i^k$). This can be the result of a single gain and its probability in case of "win all or loose all" situations, or the scalar product over a variety of possible scenarios. For the sake of simplicity, we focus on the latter. We assume a technology's risk and associated probability of failure (ρ^k) to be very high for emerging technologies in early stages of their

[8] Which holds on average in most settings, yet some situation and personal characteristics might lead to an active "risk taking" behavior (Tversky and Kahneman, 1992) and other forms of non-linear risk preferences.

life-cycle, while gradually decreasing when a technology matures. Hence, in the local minimum $\underline{x}^k$, $\rho^k = 1$; in the local maximum $\overline{x}^k$, $\rho^k = 0$; in between, it increases exponentially, as illustrated in Equation F.8.

$$\rho^k = (\frac{x - \overline{x}^k}{\underline{x}^k - \overline{x}^k})^2 \tag{F.8}$$

3.4 Investor Network effect

After developing a simple model of investments in developing technologies, including investor heterogeneity, limited search radius for investments, and limited technology forecasting capabilities, we now introduce network effects and briefly discuss resulting changes in individual and aggregated investments with respect to their amount and the resulting technological change. Such networks among financial agents can fulfill different purposes, reaching from pure information sharing to cross/lending or co/investment networks, where we shall focus on the latter one.[9] Among professional financiers, the joint investment in the same target, called "syndication", is common practice. Rationales to engage in syndicated rather that stand-alone investments are (i.) increased deal-flow, (ii.) capital-pooling, (iii.) risk-sharing, (iv.) superior joint selection of investments, (v.) reciprocity and social reasons pertaining to network position,(vi.) portfolio diversification, and (vii.) synergies in investment value-adding (Lerner, 1994). Again, we will focus on the first three rationales, and discuss possible modifications to include the latter ones.

Therefore, we introduce an adjacency matrix $\Omega = (\Omega_{ij})_{i,j}$ representing a co-investment network among financial agents, where every agent has a set of neighbors Ω_i.

When selecting the most profitable investment k, the financial agents now consider investments in their choice set χ_i carried out on their own or in a syndicate together with a co-investor j in their ego-network Ω_i. If a joint investment, for reasons we discuss later, turns out to be the most profitable one, agent i will invite j to join. In such co-investments, the joint capital endowment ($e_{i,j}$) and forecasting capability ($h^k_{i,j}$) are calculated as follows:

$$e_{i,j} = \lambda \cdot e_i + (1 - \lambda) \cdot e_j \tag{F.9}$$

$$h^k_{i,j} = \lambda \cdot h^k_i + (1 - \lambda) \cdot h^k_j \tag{F.10}$$

[9]However, an alternative model allowing for only information sharing regarding potential investments could be easily done with some minor modifications

$$c_i^k = \lambda \cdot c_{i,j}^k; \quad c_j^k = (1-\lambda) \cdot c_{i,j}^k \tag{F.11}$$

$$\pi_i^k = \lambda \cdot \pi_{i,j}^k; \quad \pi_j^k = (1-\lambda) \cdot \pi_{i,j}^k \tag{F.12}$$

However, in such syndicated investments, also asymmetric information and moral hazard issues arise. In cases when $h_i^k > h_j^k$, investor i has an advantage in the evaluation of the technology's potential compared to his co-investor j, which only can trust i's assessment. The trust the investor with lesser information has in the evaluation of his better informed peer will depend on the relationship between both, ranging in a continuum from no ($h_{i,j}^k = \arg\max[h_i^k, h_j^k]$) to full trust ($h_{i,j} = \arg\min[h_i^k, h_j^k]$). The level of trust here is represented by the parameter λ. In our simulations, λ takes the value 0.5, representing an average level of trust.

In this model, three rationales for syndication emerge. First, by capital pooling, financial agents now are able to jointly carry out huge investments which they otherwise could not stem on their own. Second, agents can benefit from teaming up with partners with superior forecasting capabilities in the particular technology to get financed. Third, they can also benefit from increased deal-flows, since their network partners might invite them to otherwise inaccessible investment opportunities.[10]

3.5 Timing: The Investment Process

The investment process is timed discretely. At the beginning of every round, financial agents consider their choice sets χ_i of potential investment targets, containing the technologies that they can spot depending on their position in the technology space and their search radius. They estimate the risk-adjusted returns on investments, both on their own (Π_i^k) or in a syndicate together with a co-investor j in their ego-network Ω_i ($\Pi_{i,j}^k$). The investment that yields the higher risk-adjusted return is the one that is made. If the technological development fails, which happens with probability ρ^k, the technology remains at its original position in the technology space. If it succeeds (with probability $1-\rho^k$), the technology develops to its new position in the technology space, climbing the fitness landscape towards the local maximum. This process is repeated until no profitable investments remain available. A visualization of an exemplary investment process to illustrate the logic can be found in figure F.8 in the appendix.

[10] We assume a unilateral initiative by investor i, where co-investor j automatically joins all invited investments which offer a positive risk adjusted rate of return.

4 Results

To put our theoretical framework and its mathematical mechanisms to a test, we ran a set of Monte Carlo simulations on different investor network structures and technology landscape complexity. Here, we ran 20 Monte Carlo simulations for 50 different landscapes, which are constructed using from 1 to 50 Gaussian mixtures to test the effects of increasing technological complexity (represented by an increasing ruggedness of the landscape by adding more Gaussian Mixtures) in investment activity. We do that in four different settings where financial agents are: (i.) unconnected who can only invest on their own, (ii.) connected in a heterogeneous (random) network, (iii.) connected with a tendency to be homogeneous in search radius, and (iv.) connected with a tendency to be homogeneous in position. We therefore create possible co-investment and information-sharing links between investors with a certain probability, which is in case (ii.) equal for all other agents, in cases (ii.) and (iv.) increasing in similarity of search radius or position in the landscape. We thereby want to mimic the potential tendency of financial agents to establish partnerships either with partners on a similar level of specialization (separation between generalists and specialists) or a similar locus of competences (clustering of investors in technology space).

We construct the different networks in the following way. In the heterogenous network all pairs of investors have an equal probability of being tied by a collaboration, which is in our case 0.5, leading also to a network with the density of 0.5. In the network homogeneous in position, this probability is weighted by the distance between the investors in the technology space. In the network homogeneous in searching radius, this probability is weighted by the absolute difference between their searching radius. The networks are computed in the following way: we start with a matrix of random numbers from a $U[0,1]$ distribution. For the homogeneous in position (search radius) network, we multiply every entry $A_{i,j}$ of the matrix by the distance between the positions (search radius) of the corresponding investors, $|x_i - x_j|$ ($|r_i - r_j|$). For the resulting matrix, the lowest half of the entries are transformed into ones, and the highest half are turned into zeros. Thus, two investors with similar positions in the landscape (search radius) are likely to be connected in the homogeneous in positions (search radius) network, while the heterogeneous network is a poisson network.

For all four network constellations, we ran 50 Monte Carlo simulations per technology landscape (of which we also have 25, constructed out of 1-25 Gaussian mixtures).

In figure F.5 we plot the development of aggregated expected benefits (sum of all investors' expected profits during the investment process as an average of all MC runs on one landscape) with increasing technological complexity. The expected profits can be seen as a measure of performance of financial agents, determining the survival and future investment capacity of the population. As expected, all constellations of networked agents outperform the unconnected ones. In relative terms, this gap increases with technological complexity. Among the different network constellations, the investor networks homogeneous in search radius in all cases perform worse, while the ones homogeneous in position mostly outperform the rest. A direct implication thereof is that investors should not exclusively strive for establishing networks among other investors of a similar type (bank with bank, VC with VC), but rather aim for building a heterogeneous network. There, best results are achieved with co-investors with a close locus of their knowledge base, where synergies of endowment and forecasting capabilities can be utilized most effectively.

In the following figure F.6 we plot the number of technological peaks discovered (meaning technologies brought to their full extent of maturity), representing a measure of technological diversity created. There we again see a tendency of networked agent populations to outperform isolated ones, even though the results among the different constellations are more ambiguous.

Finally, in figure F.7 we plot the aggregated amount of technological fitness improvements achieved by the investments, representing a measure of the overall rate of technological change. Again, networked agents tend to outperform isolated ones in financing technological change, where again the constellations homogeneous in position do best in most cases. Interestingly, networks homogeneous in search radius perform almost as weak as isolated agents – in some cases even worse. This contrasts previous findings, where all network constellations enjoyed some benefits: in terms of technological change some networks might indeed cause more harm than good. These results resembled the empirical findings of Hain and Jurowetzki (ming), who investigate the impact of different network constellations in public funded R&D projects in danish smart-grid research and suggest networks strongly controlled by incumbent actors to direct the research in more incremental trajectories. In the same way, syndicated high endowment/low forecasting investors enjoy little cooperation benefits from pooling their low forecasting capability, but pooling their endowment leads to a large expansion of investment capacity. Further, with their high joined search radius they are jointly able to cover large parts of the landscape. Yet, their little depth of technological knowledge will make them even more likely to prefer capital intensive investments in mature technology at the end of their life-cycle. Consequently, even with high overall investments, such networks will mainly channel resources into incremental innovation and neglect promising early stage technologies. This finding leads to immediate policy implications, suggesting that large investor "cartels" of big players should be considered very critically, while co-investments between high endowment investors, such as large investment banks, and specialized technology investors, such as venture capitalists, have the potential to accelerate technological change.

Our overall results indeed indicate networked investor population to outperform isolated investor performance, an effect that tends to increase with complexity of the technology landscape. We also find heterogeneous networks to show a tendency to outperform other network configurations in more complex settings. Both findings appear more pronounced for overall investment activity than for the financial agents profits. In line with innovation system literature, these results suggest that in modern complex technological system, heterogeneous networks, in this case among investors, appear to be the most conductive environment for innovation to thrive. Yet, they also suggest that heterogeneity not in all cases leads to benefits, and that homogeneity sometimes even slows down technological change.

5 Conclusion & Avenues for Future Research

In this paper we presented an agent-based simulation model of technology investment by heterogeneous and interacting financial agents. Investment decisions are explained by the topology of the technology landscape, the agents' capability to receive and interpret incomplete landscape information, and their investment capacity. We thereby aim to explain the complex relationship between investor behavior, technology characteristics, and technological change. We first focused on the general impact of different investor populations and network structures on the rate and direction of technological change, given a particular topology of the technology landscape.

We envision technological change primarily as the outcome of micro-level activities between agents conducting research and development (i.), and financial agents providing the capital to do so (ii.). In detail, we aim to explain investment decisions of heterogeneous financial agents with incomplete information regarding investment opportunities as well as their technological potential. The outcome of such search and investment processes - technological change - manifests in a realized reconfiguration of components in a complex technological system consisting of interrelated components.

Assuming analytical orthogonality between these dimensions in the short run, we attempted to formalize heterogeneous investors decision process under uncertainty and incomplete information in given innovation projects. We explain this micro-decision and the macro-implication for technological change as depending on the topology of the technology landscape, the structure and composition of the investors network, their position in technological space and degree of specialization. We are particularly interested in which network structures and compositions lead to the high rates of technological change and diversity.

The results from a Monte Carlo simulation on different investor network structures and technology landscape complexity indeed indicate networked investor population to outperform isolated investor performance, an effect that tends to increase with complexity of the technology landscape.

Our general attempt is to provide a more nuanced understanding of the interplay between technology characteristics and decision making processes of bounded rational investors and emerging characteristics of a technological system. We thereby contribute to literature on technological change as well as financial and investment theory by establishing an analytical link between them. We are also convinced that this model provides a solid basis for simulations to be done, enabling them to derive important implications for theory and practice. For policy making, it provides the potential to analyze real life investor populations and, based on the results, facilitating technological change by policies aiming to reconfigure investor network structures or by targeted public funding in problem areas.

Up to now, we made a set of simplifying strong assumptions. Yet, the provided model calls for further extensions to provide a more nuanced picture, thereby offering plenty of fruitful avenues for future research.

First, financial agents make their assessment only based on perceived technological potential of innovation projects, independent of associated research agents characteristics. In reality, such characteristics as the capabilities of an entrepreneur or management team, the financial stability of a firm *et cetera* obviously matter (Hain and Christensen, 2014). For the sake of simplicity, we assume such characteristics to be randomly distributed among research agents. However, scenarios where financial agents show preferences for certain states of such characteristics (firm size, age, balance sheet facts) which are unevenly distributed on the landscape might also offer interesting insights. Among others, it could explain why some sectors with particular characteristic mismatches are very unsuccessful in obtaining finance in spite of great technological opportunities. In the same way, relationships between research and financial agents might very well influence allocation decisions (Uzzi, 1999), in a way that former successful investments between the same pair of agents lead to the formation of relational trust and therefore preferences towards projects carried out by there research agents.

Another possible extension would be endogenous change of the agents' networks. For instance, financial agents could be allowed to reconfigure their ego-network in order to increase their short- or long-term returns. Such a model could possibly explain the path-dependent concentration of investments in certain technologies, either because they are initially very profitable and thus many financial agents establish connections to "investment experts" in that sector, or because the financial agents operating in this sector are initially well connected and thus can mobilize large investments. In the same way, research agents could reconfigure their networks for various reasons. In the former sections we already provided an overview as to how research networks might develop differently depending on industry characteristics (eg. Hain et al., 2014), the agents strategies (eg. Hain and Jurowetzki, ming), or the expected cooperation performance (eg. Balland et al., 2012). These mechanisms could also be used to explain the endogeneous formation of research networks with respect to the agent's technological competences and the associated fitness of the technology, and financial constraints.

In such a model of endogenous technological change, the agents' learning should also be included in different ways. One could be that investors are able to gradually update their position on the landscape after personal or observed successful investments. Alternatively, former investments could improve the search radius and/or forecasting capability. Both mechanisms might over time lead to situations where the attention of financial agents concentrates in particular on the past successful areas of the technology landscape.

All these extensions demonstrate the potential of an integrated framework of technological change based on the network topology within and between investor, research, and technology space to reproduce stylized facts and gain insights in the mechanisms creating them. However, while the reproduction of such stylized facts can to some extent be used to verify the proposed mechanisms, if possible one should strive for empirical verification (Pyka and Fagiolo, 2005) with real world data. Further, to use models not only as a descriptive but also predictive tool supporting future decision making, the mechanisms have to be measurable with available data. For the present framework, we indeed encounter measurement challenges in investor, research, and technology space, which we will briefly discuss now, and point towards possible solutions. Generally, network analysis is very sensitive to missing data, hence removing some important agents (nodes) or their connection (edges) in some cases dramatically alters the topology of the resulting network. This problem amplifies in dynamic complex systems, which are usually very sensitive to initial conditions. Consequently, modeling the complex dynamics of large networks *per se* has a high standard regarding the data serving as input.

In financial space, there exists, besides large scale surveys (which often suffer from missing data), very little possibilities to measure more informal networks of information sharing among investors. However, we do have well documented global data on all kind of equity investments from various commercial databases – including detailed information on all involved investors and the investment target, which can be used to construct fairly reliable historical co-investment networks. Yet, this is only the case for equity investments, such as venture capital, private equity, management-buyouts, and mergers & acquisitions. While equity investors play an important role in financing early stage innovation projects and entrepreneurship, their impact differs across countries and industries. This calls for caution when generalizing insights offered by models based on such data.

In technology space, there exist some possible ways to delineate technological systems, identify entities, map their relationships and development over time. Commonly, this is done by exploiting patent data or scientific publications (eg. Fontana et al., 2009; Verspagen, 2007) and their citation pattern. Jurowetzki and Hain (2014) take a different approach by leveraging modern advances in natural language processing and the availability of large amounts of technology related online text. Using entity extraction techniques, they identify technology terms across documents, connect them by their weighted co-occurrence in this documents, and cluster them to technological fields with dynamic community detection methods. To evaluate the "fitness" of identified technologies, Fleming and Sorenson (2001) use forward-citations a patent embodying a certain technology combination receives. While this methodology appears appropriate for empirical hypothesis testing and model verification, a long time-lag between the appearance of a technology-combination and the availability of data limits its potential as input for predictive models. Further, it only provides data on revealed technological fitness of realized technology combinations, not potential fitness of unexplored alternatives. Consequently, to make fitness landscapes and their application in the presented framework a powerful forecasting tool, there is still a lot of work to be done to find ways to construct more complete landscapes based on available real world data.

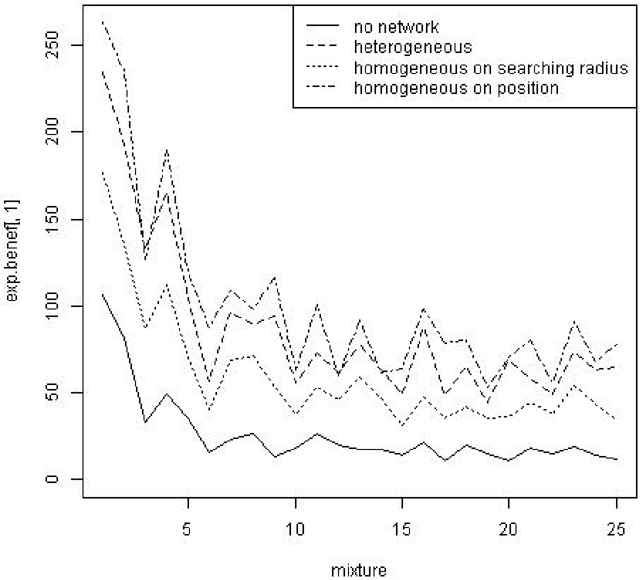


Fig. F.5: Monte Carlo simulation results on different financial agent networks and technology landscapes - Expected profits

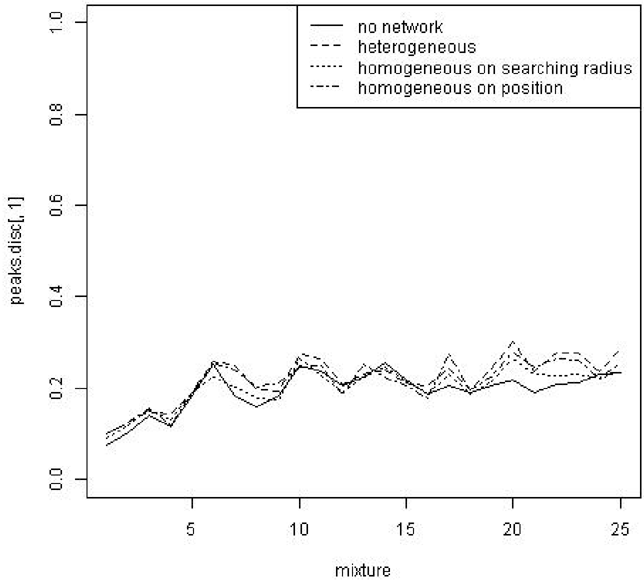


Fig. F.6: Monte Carlo simulation results on different financial agent networks and technology landscapes - Number of technology peaks discovered

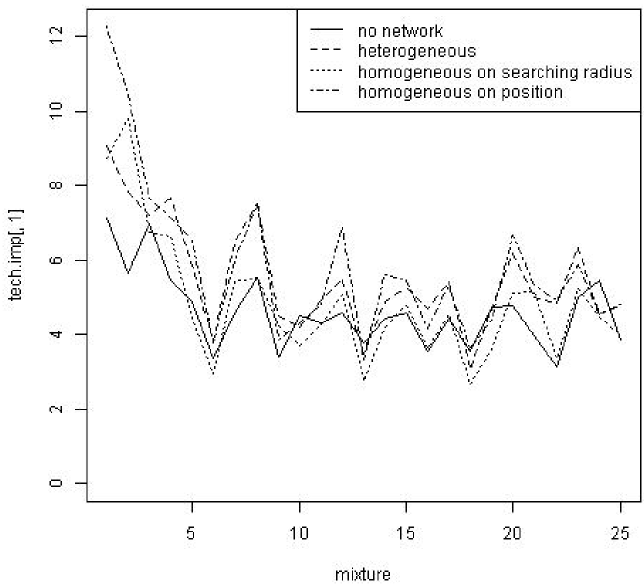


Fig. F.7: Monte Carlo simulation results on different financial agent networks and technology landscapes - Aggregated technological change

References

Amit, R., Brander, J., and Zott, C. (1998). Why do venture capital firms exist? theory and canadian evidence. *Journal of business Venturing*, 13(6):441–466.

Arrow, K. J. (1962). Economic welfare and the allocation of resources for invention. In Nelson, R., editor, *The Rate and Direction of Inventive Activity*, pages 609–625. Princeton University Press.

Arrow, K. J. (1965). Aspects of a theory of risk bearing. *Journal of Finance*, 40:1341–1352.

Balland, P.-A., De Vaan, M., and Boschma, R. (2012). The dynamics of interfirm networks along the industry life cycle: The case of the global video game industry, 1987–2007. *Journal of Economic Geography*.

Baum, J., Shipilov, A., and Rowley, T. (2003). Where do small worlds come from? *Industrial and Corporate change*, 12(4):697–725.

Beck, T. and Levine, R. (2002). Industry growth and capital allocation: does having a market-or bank-based system matter? *Journal of Financial Economics*, 64(2):147–180.

Bijker, W. E., Hughes, T. P., and Pinch, T. J. (1987). *The Social Construction of Technological Systems: New Directions in the Sociology and History of Technology*. MIT Press.

Black, B. and Gilson, R. (1998). Venture capital and the structure of capital markets: banks versus stock markets. *Journal of Financial Economics*, 47(3):243–277.

Burt, R. S. (1992). Structural holes: The social structure of competition. In Nohria, N. and Eccles, R., editors, *Networks and Organizations*, pages 57–91.

Burt, R. S. (2001). Structural holes versus network closure as social capital. *Social capital: Theory and research*, pages 31–56.

Carlsson, B. and Jacobsson, S. (1997). Diversity creation and technological systems: a technology policy perspective. *Systems of innovation: Technologies, institutions and organizations, London, Pinter Publishers*.

Casamatta, C. and Haritchabalet, C. (2007). Experience, screening and syndication in venture capital investments. *Journal of Financial Intermediation*, 16(3):368–398.

Cressy, R., Munari, F., and Malipiero, A. (2007). Playing to their strengths? evidence that specialization in the private equity industry confers competitive advantage. *Journal of Corporate Finance*, 13(4):647–669.

Dinica, V. (2006). Support systems for the diffusion of renewable energy technologies – an investor perspective. *Energy Policy*, 34(4):461–480.

Dosi, G. (1982). Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. *Research policy*, 11(3):147–162.

Dosi, G. (1988). Sources, procedures, and microeconomic effects of innovation. *Journal of economic literature*, pages 1120–1171.

Dosi, G. (1990). Finance, innovation and industrial change. *Journal of Economic Behavior & Organization*, 13(3):299–319.

Dosi, G. and Orsenigo, L. (1988). Coordination and transformation: an overview of structures, behaviours and change in evolutionary environments. In Dosi, G., Freeman, C., Nelson, R., and Soete, L., editors, *Technical Change and Economic Theory*, pages 13–37, London. Pinter Publishers.

Ferrary, M. (2010). Syndication of venture capital investment: the art of resource pooling. *Entrepreneurship Theory and Practice*, 34(5):885–907.

Fiet, J. O. (1995). Reliance upon informants in the venture capital industry. *Journal of Business Venturing*, 10(3):195–223.

Fleming, L., Mingo, S., and Chen, D. (2007). Collaborative brokerage, generative creativity, and creative success. *Administrative Science Quarterly*, 52(3):443–475.

Fleming, L. and Sorenson, O. (2001). Technology as a complex adaptive system: evidence from patent data. *Research Policy*, 30(7):1019–1039.

Fontana, R., Nuvolari, A., and Verspagen, B. (2009). Mapping technological trajectories as patent citation networks. an application to data communication standards. *Economics of Innovation and New Technology*, 18(4):311–336.

Freeman, C. (1987). *Technology Policy and Economic Performance: Lessons from Japan*. Pinter Publishers, London.

Freeman, J., Carroll, G., and Hannan, M. (1983). The liability of newness: Age dependence in organizational death rates. *American Sociological Review*, pages 692–710.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, 78(6):1360–1380.

Hain, D. S. (Mimeo). Networks: The missing link between innovation finance and technological change. a conceptual framework. working paper.

Hain, D. S., Buchmann, T., Kudic, M., and Müller, M. (2014). Exploring the evolution of innovation networks in science-driven and scale-intensive industries: New evidence from a stochastic actor-based approach. *IWH Discussion Paper 1/2014*.

Hain, D. S. and Christensen, J. L. (2014). The small, the young and the innovative. a longitudinal analysis of constraints on external innovation financing. submitted for publication.

Hain, D. S. and Jurowetzki, R. (forthcoming). Incremental by design? on the role of incumbents in technology niches - an evolutionary network analysis. *Journal of Evolutionary Economics*.

Hanusch, H. and Pyka, A. (2007a). *Elgar companion to neo-Schumpeterian economics*. Edward Elgar Publishing.

Hanusch, H. and Pyka, A. (2007b). Principles of neo-schumpeterian economics. *Cambridge Journal of Economics*, 31(2):275–289.

Hochberg, Y. V., Ljungqvist, A., and Lu, Y. (2007). Whom you know matters: Venture capital networks and investment performance. *The Journal of Finance*, 62(1):251–301.

Hughes, T. P. (1987). *The Evolution of Large Technological Systems*, pages 51–82. The MIT Press.

Jurowetzki, R. and Hain, D. S. (2014). Mapping the (r-) evolution of technological fields – a semantic network approach. In Aiello, L. M. and McFarland, D., editors, *Social Informatics*, volume 8851 of *Lecture Notes in Computer Science*, pages 359–383. Springer International Publishing.

Kauffman, S. and Macready, W. (1995). Technological evolution and adaptive organizations: Ideas from biology may find applications in economics. *Complexity*, 1(2):26–43.

Kauffman, S. A. (1993). *The origins of order: Self-organization and selection in evolution*. Oxford university press.

Kenney, M. (2011). Venture capital investment in the greentech industries: a provocative essay. In Wüstenhagen, R. and Wuebker, R., editors, *Handbook of Research on Energy Entrepreneurship*, page 214. Cheltenham, UK: Edward Elgar Publishing.

King, R. and Levine, R. (1993). Finance, entrepreneurship and growth. *Journal of Monetary economics*, 32(3):513–542.

Klepper, S. (1997). Industry life cycles. *Industrial and corporate change*, 6(1):145–182.

Knight, F. H. (1921). *Risk, Uncertainty and Profit*. University of Chicago Press.

Kortum, S. and Lerner, J. (1998). Does venture capital spur innovation? NBER Working Paper 6846: Available at: http://www.nber.org/papers/w6846.

Kortum, S. and Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *RAND Journal of Economics*, pages 674–692.

Lerner, J. (1994). The syndication of venture capital investments. *Financial Management*, pages 16–27.

Levinthal, D. A. (1997). Adaptation on rugged landscapes. *Management science*, 43(7):934–950.

Lundvall, B.-Å. (1992). *National Systems of Innovation: Toward a theory of innovation and interactive learning*. London: Pinter Publishers.

Malerba, F. (2002). Sectoral systems of innovation and production. *Research policy*, 31(2):247–264.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization science*, 2(1):71–87.

Mazzucato, M. (2011). The entrepreneurial state.

Merton, R. K. (1957). The role-set: Problems in sociological theory. *British journal of Sociology*, pages 106–120.

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2):187–221.

Nelson, R. R. (1959). The simple economics of basic scientific research. *The Journal of Political Economy*, 67(3):297–306.

Nelson, R. R. (1993). *National innovation systems: a comparative analysis*. Oxford University Press, USA.

Nelson, R. R. (1994). The co-evolution of technology, industrial structure, and supporting institutions. *Industrial and corporate change*, 3(1):47–63.

Perez, C. (2002). *Technological revolutions and financial capital: The dynamics of bubbles and golden ages*. Edward Elgar Publishing.

Perez, C. (2004). Finance and technical change: A neo-schumpeterian perspective. In Hanusch, H. and Pyka, A., editors, *The Elgar Companion to Neo-Schumpeterian Economics*. Edward Elgar, Cheltenham.

Perez, C. (2010). Technological revolutions and techno-economic paradigms. *Cambridge Journal of Economics*, 34:185–202.

Powell, W., Koput, K., and Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative science quarterly*, pages 116–145.

Pratt, J. W. (1964). Risk aversion in the small and in the large. *Econometrica: Journal of the Econometric Society*, pages 122–136.

Pyka, A. (2002). Innovation networks in economics: from the incentive-based to the knowledge-based approaches. *European Journal of Innovation Management*, 5(3):152–163.

Pyka, A. and Fagiolo, G. (2005). Agent-based modelling: A methodology for neo-schumpeterian economics. Discussion Paper Series 272, University of Augsburg, Department of Economics.

Rajan, R. G. and Zingales, L. (2001). Financial systems, industrial structure, and growth. *Oxford review of economic Policy*, 17(4):467–482.

Reagans, R. and McEvily, B. (2003). Network structure and knowledge transfer: The effects of cohesion and range. *Administrative Science Quarterly*, 48(2):240–267.

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*, volume 55. Harvard University Press: Cambridge, Mass. (originally published in German in 1911; reprinted by Transaction Publishers, New Brunswick, New Jersey in 1997).

Schumpeter, J. A. (1942). *Capitalism, Socialism and Democracy*. Harper, New York.

Simmel, G. (1955). The web of group affiliations. *Conflict and the web of group affiliations*, pages 125–95.

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1):pp.99–118.

Stiglitz, J. and Weiss, A. (1981). Credit rationing in markets with incomplete information. *American Economic Review*, 71(3):393–410.

Tversky, A. and Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *science*, 185(4157):1124–1131.

Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, 5(4):297–323.

Tylecote, A. (2007). The role of finance and corporate governance in national systems of innovation. *Organization Studies*, 28(10):1461–1481.

Utterback, J. (1994). *Mastering the dynamics of innovation*. Harvard Business Press, Boston MA.

Uzzi, B. (1996). The sources and consequences of embeddedness for the economic performance of organizations: The network effect. *American sociological review*, 61(4):674–698.

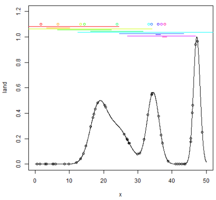
Uzzi, B. (1997). Social structure and competition in interfirm networks: The paradox of embeddedness. *Administrative Science Quarterly*, pages 35–67.

Uzzi, B. (1999). Embeddedness in the making of financial capital: How social relations and networks benefit firms seeking financing. *American sociological review*, pages 481–505.

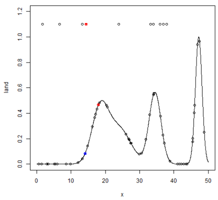
Verspagen, B. (2007). Mapping technological trajectories as patent citation networks: A study on the history of fuel cell research. *Advances in Complex Systems*, 10(01):93–115.

Winter, S. G. (2006). Toward a neo-schumpeterian theory of the firm. *Industrial and Corporate Change*, 15(1):125–141.

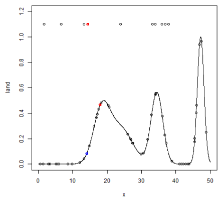
Appendix



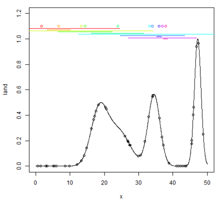
(a) Period 1.0 - Initial Landscape



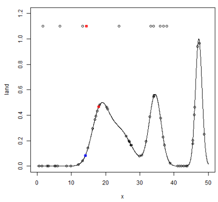
(b) Period 1.1 - Investors exp. Returns



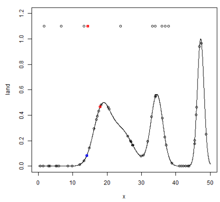
(c) Period 1.2 - Investment choice, repositioning



(d) Period 1.0 - Initial Landscape



(e) Period 1.1 - Investors exp. Returns



(f) Period 1.2 - Investment choice, repositioning

Fig. F.8: Illustration of a 4 stage investment process, 2 rounds

This figure illustrates an investment process at 2 exemplary investment rounds. Period .0 illustrates an investment rounds initial conditions, where investors as well as innovation projects representing possible investment opportunities are placed on the landscape. The colored lines below the investors illustrate their search radius, determining which potential innovation projects are visible in their choiceset. In period .1, an investor is randomly selected and assesses the available projects regarding their expected risk adjusted rate of return. In period .2, the investors project of choice (with the highest returns) is (in case of success) moved to its new position on the technology landscape.