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An Agent-Based Simulation

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Abstract: In this paper, we investigate which characteristics of technological and financial systems might be conductive for technological change. We are particularly in how the interplay between capabilities, resources and networks among investors with the complexity and maturity of technologies affect the rate and direction of investments in potential innovation projects. To do so, we present an agent-based simulation model of technology investment by heterogeneous financial agents connected in a co-investment network. 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 fitness. Subject to imperfect information and bounded rationality, financial agents are heterogeneous in their (i.) their position and "search radius" on the landscape, determining the potential investment targets they are able to spot, and (ii.) "forecasting ability", determining the accuracy of their prediction of achievable technological fitness. We observe which population of financial agents lead to high rates of technological change and diversity, and prevents technologies from getting stuck in the financial "valley of death". 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 lead to the high rates of technological change and diversity on a given technology landscape. Results from a Monte Carlo simulation indicate networked investor population to outperform the case of isolated stand-alone investors, in terms of investor benefits as well as achieved technological change. Yet, we also find evidence for the existence of a financial "valley of death" - a certain stage in the technology life-cycle where its characteristics discourage further investments, thereby making the technology likely to "die" due to underinvestment. While encouraging investments in early stages, the effect of co-investment networks does not prevent this phenomenon to occur.

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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 syndication 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. We further compare the performance (in terms of investor profits as well as achieved technological change) of different populations and network typologies of financial agents on landscapes with increasing technological complexity.

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 indicate networked investor population to outperform the case of isolated stand-alone investors, in terms of investor benefits as well as achieved technological change. Yet, we also find evidence for the existence of a financial "valley of death" - a certain stage in the technology life-cycle where its characteristics discourage further investments, thereby making the technology likely to "die" due to underinvestment. While encouraging investments in early stages, the effect of co-investment networks does not prevent this phenomenon to occur.

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 further inform the ongoing discussion on the interplay between network structure and composition. 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 3 its mathematical formalization. Section 4 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, recognized as the major 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.[1] 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 major 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 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 (Hall, 2010; Hall and Lerner, 2009; Tylecote, 2007) influence the rate and direction of technological change.

In the following, we elaborate on what we believe to be a crucial yet underexplored determinant of technological change: How the composition of investors with heterogeneous resource

[1] 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.

endowments impacts investment patterns in technologies with certain characteristics, and how this is mediated by information-sharing and co-investment networks. Further, does this effect differ when increasing the complexity of technology? Before clarifying the mechanics and other mathematical details of the simulation model, we will proceed with conceptually establishing this link between investor characteristics, networks, and resulting investments in technological change in a bigger context.

2.1 The Dimensions of Technological Change

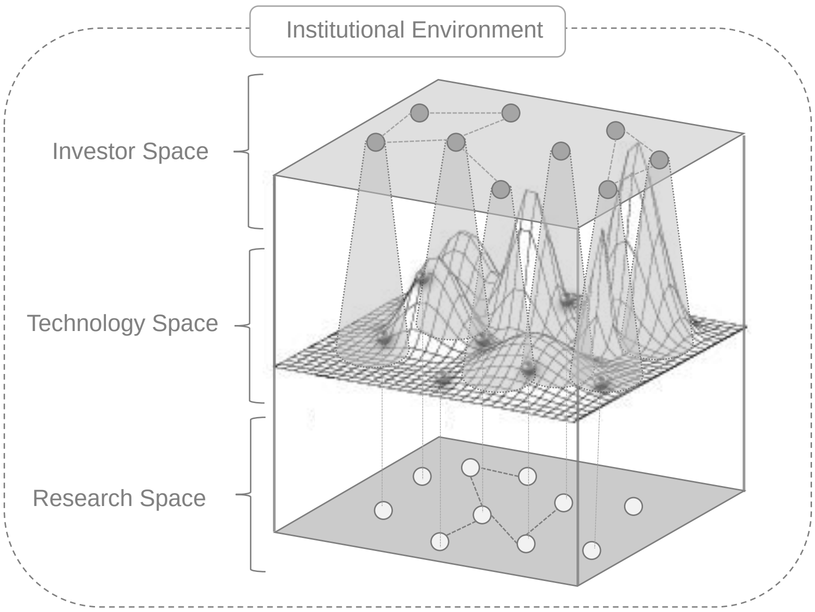
Following Schumpeter's conceptualization of the entrepreneur-banker (and broader, finance and economic progress) duality, we envision technological change primarily as the outcome of micro-level activities between (i.) agents developing invention by conducting research and development, and financial agents providing the capital to do so (ii.). In line with his neo-schumpeterian heritage (eg. Hanusch and Pyka, 2007a; Winter, 2006) we see this relationship to be embedded in a 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. This is illustrated in figure 1.

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). Here we see research, as well as financial space, to be populated by respective agents - investors and researchers - which are connected by certain cooperation pattern.

[2]For a more exhaustive discussion on these dimensions, their theoretical foundation and interplay, consider Hain (2016)

Figure 1: Linking Investment and Research on the Technology Landscape. Adapted from Hain (2016)



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 view of the technology 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 independent 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, 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,

[3]However, in later sections we discuss possible extensions, including feedback loops between investor and research activities and networks.

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, and (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. 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 (Schumpeter's MARK I mode of innovation) as well as larger companies (Christensen and Hain, 2015; Hain and Christensen, 2014). Nevertheless, we obviously exclude a fair share of technological progress happening in big multinational enterprises that are able to fully finance their research endeavors internally with means of accumulated profit (Schumpeter's MARK II mode of innovation). In this model, we treat activity in research space as a black-box, and assume the behavior of research agents as given. As determinant in the model, only their output in terms of exogenously proposed innovation projects searching for finance enters.

2.3 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 envi-

[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).

ronmental 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 (Jurowetzki and Hain, 2014). 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 (Christensen and Hain, 2014; Nogueira et al., 2015). Consequently, the *ex-ante* prediction of research outcome in this area appears to be impossible without immense technological knowledge, a fact that for instance daunts many financial agents to invest in emerging renewable energy technologies (Kenney, 2011).

2.4 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. 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 (Hain et al., 2016; Hain and Jurowetzki, 2015), 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 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 1.

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 1:

$$\Pi_i(\pi_i, \varphi_i) = \sum_{i=1}^{n} \frac{\pi_i \varphi_i}{N} \tag{1}$$

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 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 such as VCs 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.

$$\Pi_i(\pi_i, \varphi_i) = \sum_{i=1}^{n} \frac{\pi_i \varphi_i}{N}(1 - var(\pi_i)\alpha^k) \tag{2}$$

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 proba-

[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 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).

bility of different outcome states, nor the characteristics of this states can be *ex-ante* quantified. For investments in emerging technologies, we attribute this prediction deficit 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. First, they might specialize on investments in a limited 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.

Second, 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, while highly focused technology specialists will have only a very limited view of the landscape and resulting investment opportunities.

2.5 Investor Networks in Innovation Finance

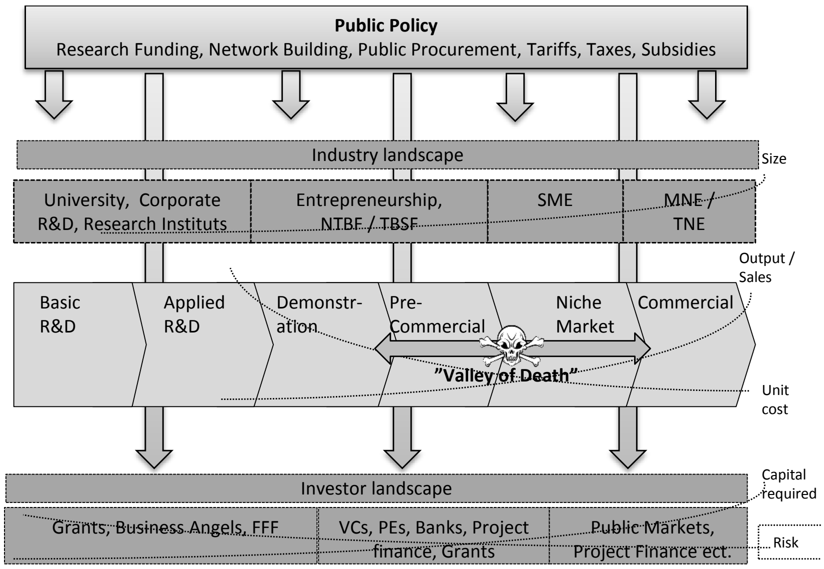
In addition to internally accumulating technological knowledge, financial agents also use their network to access external information of their cooperation partners. However, establishing and maintaining relationships to other agents usually comes with a cost, so agents will not indefinitely expand their 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). A recent stream of research integrates both lines of arguments by investigating the interaction between network structure and composition (eg. Rafols and Meyer, 2010; Rakas and Hain, 2016; Ter Wal et al., 2016). 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.

2.6 Investments and the Technology Life-Cycle

Without the commitment of financial resources, ideas remain ideas, independent of their potential. One of the main selection mechanisms innovation projects have to face, is the allocation decisions of potential investors (Dosi, 1990). 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. As argued throughout this paper, investors are heterogeneous not only in their resource endowment and capabilities, but also in applied investment selection routines. Likewise, it is well established in literature on the history of technology, economics, and technology management, that during their life-cycle, technologies undergo qualitative changes which alter their internal characteristics and external potentials (Afuah and Utterback, 1997; Kaplan and Tripsas, 2008; Klepper, 1997).

We here focus on the change of two characteristics of particular importance for the formerly discussed selection criteria of investors, the risk and scale of investments associated with certain stages of the technology life-cycle. First, while maturing, the risk of failure in further development of technologies tends to decrease. 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. This relationship between technology characteristics, associated unit carrying out innovation projects (research agents), and providers of capital (financial agents) is illustrated in figure 2.

Figure 2: Investment, Investor, and Research Characteristics during the Technology Life-Cycle. . Adapted from Hain (2016) and Christensen and Hain (2014)



An important consequence of cross-sectional investor heterogeneity and longitudinal technology heterogeneity throughout it's life-cycle is the potential of total or temporary mismatches between investor selection criteria and technology characteristics, leading to a systematic underinvestment of technologies in certain stages of 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 (Wüstenhagen and Menichetti, 2012), when capital requirements get to high for specialized early stage investors but the technology risk is still unacceptably high for general risk-averse late-stage investors with suitable capacity.

3 The Model

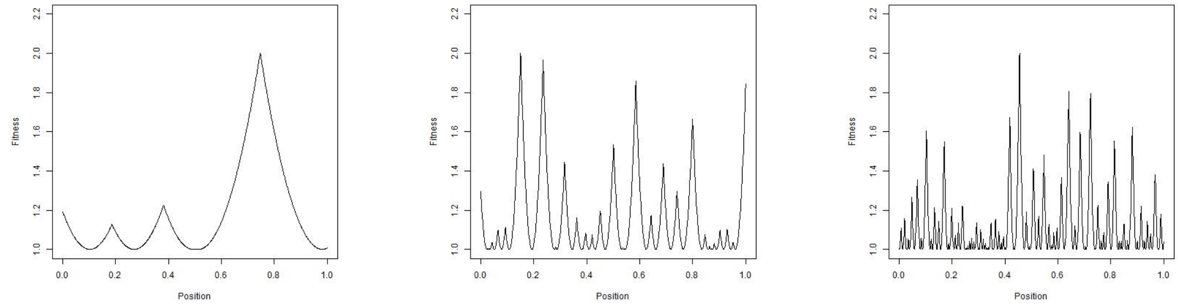
Based on the theoretical considerations in the previous section, in the following we specify our agent-based simulation model. We do so by first specifying the main variables and initial conditions of the technology fitness landscape and the involved agents, followed by the timing and mechanics of the investment process. Finally, we introduce the option that financial agents can form networks and co-invest with each others, and elaborate on resulting changes for the model.

3.1 Initial Conditions

The Technology Landscape

First, we create a two-dimensional fitness landscape representing the space of a technological system, where different technology configurations are ordered by 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 appropriately 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 3.

Technological progress here is associated with the search of configurations which increase a technology's current fitness level. The path from a local minimum $\underline{x}^k$ towards the closest local maximum $\overline{x}^k$ can be envisioned as a certain technological trajectory, and the process of gradual improvement over time from the minimum towards the maximum as a certain technology's life-cycle. The relative height of a technology in this life-cycle represents its current degree of



(a) Mixture of 5 Gaussian (b) Mixture of 30 Gaussian (c) Mixture of 90 Gaussian

Figure 3: Different technology landscapes with 5, 30, 90 Gaussian Mixtures

maturity. Consequently, at a local optimum a technology has reached full maturity and exhausted its trajectory, leaving no potential for further innovation.[7]

The Innovation Projects

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 project's current technological configuration as basis for the further search for improvement on the technological trajectory leading to the closest local maximum. Together, the potential innovation projects form the choice-set χ which includes all possible investments in technology projects within a certain technological system. For the sake of simplicity, the amount and position of innovation projects in χ is given exogenous, assuming independence between investment decisions and research efforts.[8]

The Financial Agents

Financial agents i, the main protagonists of our model, are heterogeneous in the following characteristics:

First, their position p_i on the fitness landscape represents their locus of technological expertise. Consequently their own search strategy, visibility among potential investment targets seeking for funding, tends to concentrate around this position. Second, their extend of specialization and

[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.

[8] Yet, the interaction between investor signals with respect to investment preferences and research efforts would provide a promising avenue for future research.

resulting "breadth" of technological knowledge is determined by the search radius r_i, where low values indicate the focus on a narrow set of technologies, and high ones a broad and general overview on large parts of the technology landscape. Third, the forecasting ability h_i represents the financial agents' "depth" of knowledge, determining their capabilities of predicting the further development of technologies. While the search radius reflects the agents' insights on the x-axis of the landscape, the forecasting ability reflects their insight on the y-axis, consequently the extend to which they can assess the height of the local peak of a certain technology and the resulting profit opportunities of an investment in it.

We assume a trade-off between search radius (knowledge breadth) and forecasting ability (knowledge depth), 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. We model that as a simple inverse relationship between search radius and forecasting ability. 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. The search radius will serve as a reverence point for the calibration of the other characteristics. The relationship between a financial agents position, search radius and forecasting ability for a particular project is formalized in equation 3:

$$h_i^k = (1 - 2r_i) \cdot (1 - |x_i - x^k|)^2 \tag{3}$$

Finally, financial agents differ in their capital endowment e_i, which determines the amount they are willing or able to invest in an innovation project. To depict some stylized facts on investors, we assume more generalized investors such as investment banks to have a higher capital endowment than investors specialized on narrow technological fields, such as venture capitalists. Moreover, the endowment of any firm has an upper bound in a third of $\overline{e}$, where $\overline{e}$ is the cost of going from biggest technological improvement possible in the landscape. This positive relationship between search radius and capital endowment is formalized in equation 4

$$e_i = \frac{2r_i \cdot \overline{e}}{max(f) * 3} \tag{4}$$

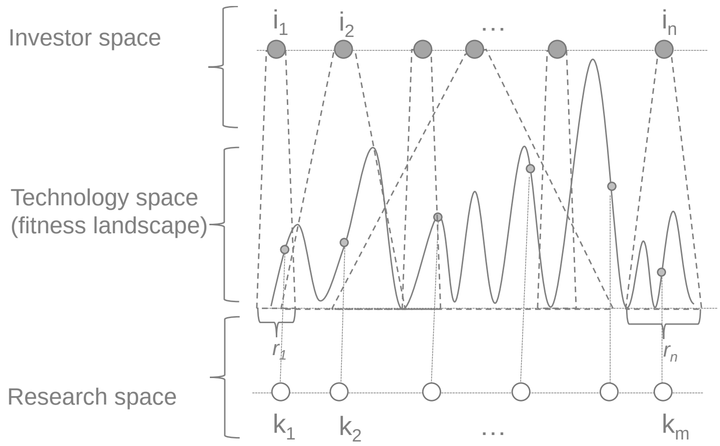
3.2 Characteristics and Mechanics the Investment Process

In the following, we outlay the investment process of financial agents and the corresponding impact on technological change, as reflected by improving fitness levels of innovation projects. We do so by first determining the financial agents limited choice-set of possible investment opportunities reflected by innovation projects, depending on their position on the technology landscape and their search radius. In a next step, we outlay the financial agents conditional assessment of expected returns and resulting investment selection, depending on the agents conditional forecasting capabilities, the innovation projects position in the technology life-cycle, and the highest achievable technological fitness in the chosen technological trajectory.

Landscape Scanning and Investment Choice-set of Financial Agents

As a first necessary condition for an investment in an innovation project to take place, the respective investor has to be aware of the particular investment opportunity. Assuming the market for technology investments to be information imperfect, potential investments are discovered by the financial agents via active own search, signals from their information network or investment seeking research agents.[9]

Figure 4: Investors view on the technology landscape



[9]We here focus on the financial agents active search process, yet discuss the possibility of information sharing networks between financial agents as well as with research agents later on.

To illustrate this process of market-scanning, one can imagine financial agents to observe the technology landscape from a birds-eye perspective, as illustrated in figure 4. If an investment-ready innovation project k falls into a financial agent's i choice-set χ_i depends on the project's position x^k on the technology landscape, the financial agents position x_i and search radius r_i, as formalized in equation 5

$$\chi_i \subseteq \chi \quad where: \; x_i - r_i \leq x^k \leq x_i + r_i \tag{5}$$

Investment Decision

After a financial agent's choice set χ_i is defined, the agent evaluates the profitability of available investments and chooses the most attractive one. We assume agents to primarily aim to maximize the risk-adjusted rate of return on investments (Π_i^k) by selecting among the potential options k what is perceived as the most profitable one, as stated in equation 6:

$$\arg\max_{k \in \chi_i}[\Pi_i^k(\pi_i^k, \rho_i^k, c_i^k) = (1 - \rho_i^k) \cdot \pi_i^k - c_i^k \quad where: c_i^k \leq e_i] \tag{6}$$

The investor specific risk-adjusted rate of return of a particular investment here depends on the costs of the investment c_i^k, the gains in case of success π_i^k, and the probability of failure ρ_i^k, which will be specified in the following. The amount financial agent are able to invest into an innovation project – and thereby the possible costs and benefits – is limited by two factors. First, the costs of an investments cannot exceed the agents capital endowment e_i. Second, the increase of the innovation projects technological fitness due to the investment can also not be higher than the financial agents forecasting capability h_i^k on the particular investment. We hereby appreciate the uncertainty of investments in innovation projects caused by a lack of knowledge and information. Financial agents will only invest in innovation project to the extend they can be confident about its possible development.

Besides the agent-specific limitations in forecasting capability and investment capacity, the financial agents investment evaluation depends on the fitness and maturity of the innovation project. While its fitness level is absolute, its maturity represents its relative point in the technology life cycle between the local minimum $\underline{x}$ and maximum $\overline{x}$. In the following, we discuss the components of this evaluation in detail. Further, figure 5 provides a graphical illustration of the relation between a technology's maturity and the associated costs, probability of failure, and potential returns of investments.

The costs $c(x \rightarrow y)$ of increasing a the fitness of a certain technology from its original position x to a new position y depend on the innovation project's post-investment position in the technology life-cycle, and the relative progress in the technology life cycle due to the investment. Consequently, in our model the costs of increasing a technologies fitness are not depending on the achievable fitness level, but solely on the technologies maturity, where early stage technologies are associated with low and mature technologies with high capital intensity and resulting costs of further improvement. We model the costs to increase non-linear during the technology life cycle, as formalized in equation 7.

$$c(x \rightarrow y) = ((f(y) - f(x)) \cdot \frac{f(y) - f(\underline{x})}{f(\overline{x}) - f(\underline{x})})^2 \tag{7}$$

Yet, investing in innovation is related with higher risk and uncertainty (Dosi and Orsenigo, 1988) leading to a higher variance of returns. Such risks obviously enter the investors calculation, 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). 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, in our model we assume investment-specific variables to be randomly distributed among innovation projects, and focus on the financial agents evaluation of technology risk. As a simple rule, financial agents will require higher returns for riskier investments in order to maintain a certain level of average returns, as indicated in equation 6.[10] 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 former.

We assume an innovation project's risk and associated probability of failure ($\rho(x)$) to be very high for emerging technologies in early stages of their life-cycle, while gradually decreasing when

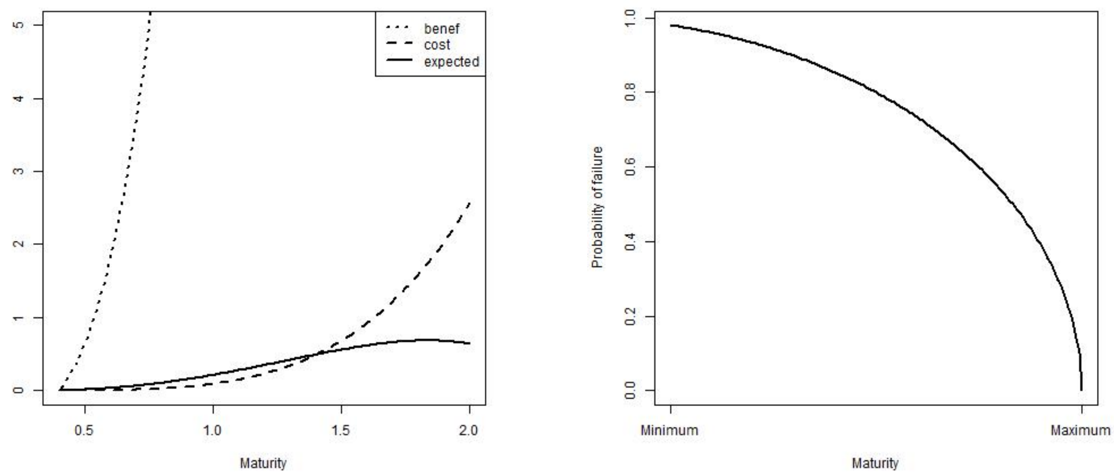
[10] Which holds on average in most settings, yet some situation and personal characteristics might lead to an active "risk taking" behavior (Tversky and Kahneman, 1992) and other forms of non-linear risk preferences.

a technology matures. Hence, in the local minimum $\rho(\underline{x}) = 1$; in the local maximum, $\rho(\overline{x}) = 0$; in between, it increases exponentially, as illustrated in equation 8:

$$\rho(x) = \sqrt{1 - \frac{(f(x) - f(\underline{x}))^2}{(f(\overline{x}) - f(\underline{x}))^2}} \tag{8}$$

Finally, the financial agents gain $\pi(x \to y)$ from an investment (in case of success) 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 innovation project. In this model we focus solely on the latter and assume the others as randomly distributed among innovation projects. In our model, the gains of an investment increase non-linear as a function of the post-investment achieved fitness level y, the increase of fitness level due to the investment ($\Delta x \to y$), and the relative increase in the technology life cycle ($\Delta x \to y$ weighted by the distance between local minimum $\underline{x}$ and maximum $\overline{x}$). Consequently, larger investments increasing the absolute fitness and relative maturity to a large extend appear to be more attractive for financial agents, as stated in equation 9:

$$\pi(x \to y) = \frac{2\, c(x \to y)}{(f(y) - f(x))(1 - \rho(x))} \tag{9}$$



(a) Costs, expected and real (in case of success) returns

(b) Probability if failure

Figure 5: Characteristics of investments by maturity of technology

Timing of the Investment Process

The investment process is timed discretely. Every round, a randomly chosen financial agent gets the opportunity to execute one investment in an innovation project from the current individual choice sets χ_i, as determined in equation 5. From this set, the agent chooses the investment offering the estimated highest positive risk-adjusted returns Π_i^k as stated in equation 6, and pay the associated investment costs c_i^k upfront. In the case no investment offering positive estimates of returns is available, no investment is made.

The next step determines the failure (with probability ρ^k) or success with (probability $1 - \rho^k$) of the invested innovation project. If the technological development fails, the technology remains at its original position in the technology space, and the project is henceforth excluded from the choiceset of the financial agent that experienced the failure.[11] If it succeeds, the technology develops to its new position in the technology space, climbing the fitness landscape towards the local maximum, and the investors reap the gains π_i^k. This process is repeated until no profitable investments for any financial agent is available anymore. A visualization of an exemplary investment process illustrating it's logic can be found in figure 9.

3.3 Investor Network Effect

After developing a simple model of technological change as a consequent of investments by heterogeneous isolated financial agents, in a next step we introduce the possibility of co-investments within a network of financial agents.[12] 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 put forward in the investment literature 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 four rationales, and discuss possible modifications to include the latter ones.

[11] In this initial version of the model, we exclude population dynamics of financial agents as well as innovation projects. Consequently, possible project failures have no effect on the existence of the exogeneously given population of agents and projects.

[12] While it is the case in our model, in reality such networks among financial agents not necessarily have to be limited on formal co-investments, but also include more informal interaction such as cross-referencing of investment opportunities and general information sharing.

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. Such networks of potential co-investors can vary in their topology, as we will discuss later. Up to now it is of relevance that all neighboring financial agents in Ω_i represent potential co-investors. This leads to the following changes in the investment process:

When selecting the most profitable investment k, the financial agents now additionally consider for every investment in their choice set χ_i the option of carrying it out alone or in a syndicate together with the potential co-investors j in their ego-network Ω_i. If a co-investment turns out to be the most profitable one ($\Pi^k_{i,j} > \Pi^k_i$), financial agent i will invite j to join the investment. 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.

While the equation for the risk-adjusted rate of return in syndicates $\Pi^k_{i,j}$ is calculated in the same way as for the one stand-alone investments Π^k_i, the joint capital endowment ($e_{i,j}$) as well as forecasting capability ($h^k_{i,j}$) differ from the financial agent i's characteristics in the following way.

The joint endowment, as illustrated in equation 10, simply represent the pooled endowment of both financial agents.

$$e_{i,j} = e_i + e_j \tag{10}$$

Now, both financial agents can join their forecasting capability to evaluate the innovation projects post-investment performance. However, in such syndicated investments, also asymmetric information and moral hazard issues arise. In cases when $h^k_i > h^k_j$, agent 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 agent 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 ($h^k_{i,j} = \arg\max[h^k_i, h^k_j]$) to full trust ($h_{i,j} = \arg\min[h^k_i, h^k_j]$),[13] as formalized in equation 11:

$$h^k_{i,j} = \lambda \cdot h^k_i + (1 - \lambda) \cdot h^k_j \tag{11}$$

[13] In our model, we use an "average" trust level of 0.5. Yet, in future research it would be interesting to explore the effect of stronger or weaker ties between financial agents, and the associated changes in relational trust, on investment behavior.

In this model, three rationales for syndication emerge. First, by capital pooling, financial agents now are able to jointly carry out larger investments which they otherwise could not stem on their own. Second, agents can benefit from better forecasts when teaming-up with agents with superior forecasting capabilities in the innovation projects technology space. Third, financial agents can also benefit from increased deal-flows, since their network partners might invite them to otherwise inaccessible investment opportunities.

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.

To capture the effect of increasing complexity of the techno-economic system, we create 50 different landscapes, which are constructed using from 1 to 50 Gaussian mixtures, leading to an increasing ruggedness of the landscape by adding more Gaussian mixtures. Higher complexity here is associated with a larger amount of potential technological trajectories with peaks of varying height. As a result, a broad investor coverage with the right forecasting capability and investment capacity of the landscape becomes instrumental for technological change.

To test the effect of varying network structures on investments technological change, we further introduce four network typologies, 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.

The outcomes of a simulation model capturing the above discussed characteristics of a techno-economic system are obviously to a large extend dependent on the initial conditions, namely the topology of the landscape, the allocation of innovation projects and financial agents on it, and the agents particular network structure. Since the success of an investment is a probabilistic event, even the same initial conditions can lead to broadly varying outcomes. Consequently, we ran for every of the four different network constellations on every level of landscape complexity (where we have 50, corresponding to landscapes with 10 to 500 Gaussian mixtures, increasing in intervals of 10) of financial agents 50 Monte Carlo simulations with varying initial conditions. The results are discussed in the following.

In figure 6 we plot the development of aggregated expected risk-adjusted 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 benefits can be interpreted on how profitable certain landscape and network configurations appear to financial agents, which should correspond to higher investment activity. When looking at investments of isolated investors, we interestingly find first hints of an "inverted U-shape" relationship between technological complexity and potential investment benefits, indicating that both very low and high levels of complexity offer less potential for profitable investments. As expected, we clearly see all three settings with connected and co-investing financial agents to clearly outperform the case of isolated ones, with an order of magnitude of roughly 30 percent. While we observe a slight tendency of heterogeneous network structures to outperform the ones homogeneous in position or search radius, this marginal differences appear to not carry economic significance. In terms of incentives offered for financial agents to invest, it appears that networks and the possibility to pool capabilities and resources *per se* provide benefits, independent of their composition.

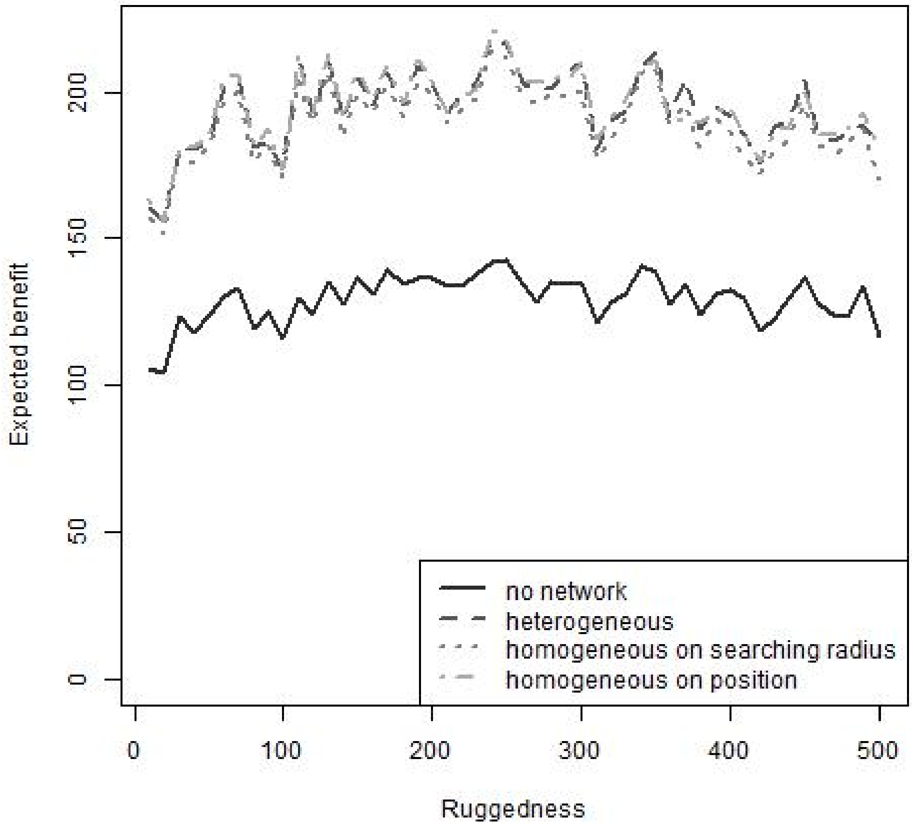


Figure 6: Monte Carlo simulation results on different financial agent networks and technology landscapes - Expected benefits

In figure 7 we plot the aggregated amount of technological fitness improvements achieved by the investments, representing a measure of the overall rate of technological change happening in the system due to investment activities. Again, networked agents tend to outperform isolated ones in financing technological change, with an even higher magnitude. Consequently, the gains of investor networks become even more apparent in fostering technological change than boosting the financial agents profits. Among the different network constellations, the investor networks homogeneous in search radius tend to perform worse, while the ones heterogeneous in position and search radius mostly outperform the rest. Even though slightly more pronounced that for the financial agents benefits, the difference yet appears small and of questionable economic significance. A first implication of these findings is that policy conductive for technological change should foremost incentive syndicated rather than isolated investments. Taking into account further long-term benefits not captured in this model, such as the establishment of informal information sharing networks among investors, the effect might even be stronger. Further, such initiatives should not exclusively strive for establishing networks among investors of a similar type (bank with bank, VC with VC). Rather, 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.

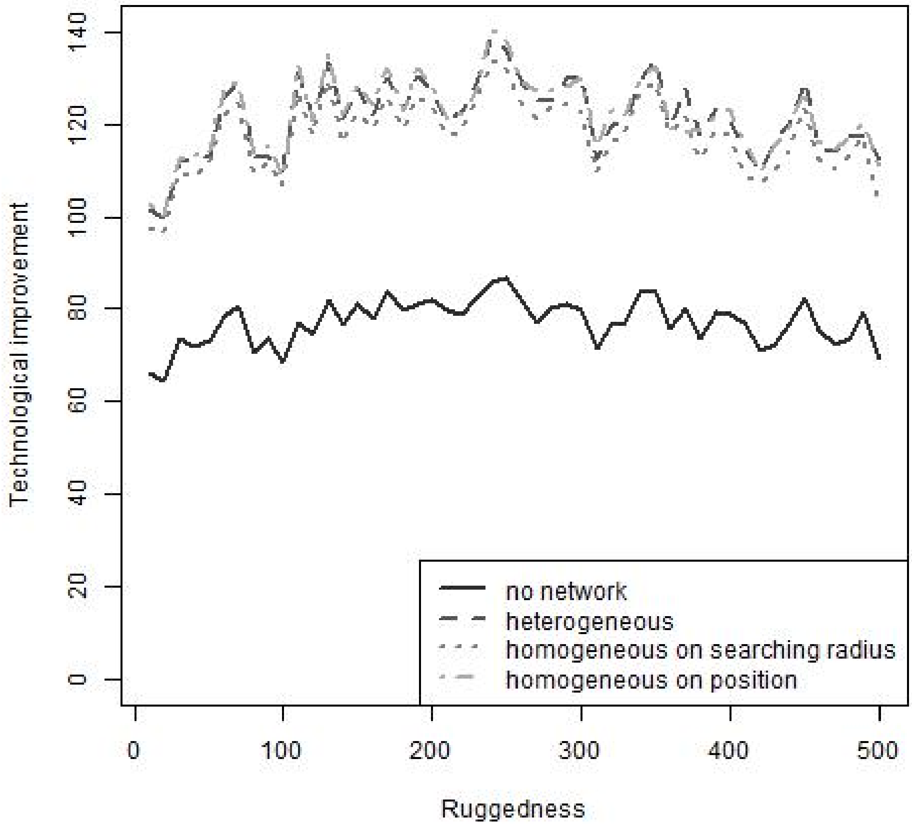


Figure 7: Monte Carlo simulation results on different financial agent networks and technology landscapes - Aggregated technological change

Finally, in figure 8 we plot the number of technological peaks discovered (meaning technologies brought to their full extent of maturity), representing a measure of technological diversity created. As to be expected, the number of technological peaks reached increases with the complexity of the landscape, just because in a more complex one, there are by construction more peaks to discover. Surprisingly and in contrast to former results, the effects of co-investment networks completely disappear. The intuitive paradox of higher benefits and technological change while similar number of technologies brought to full maturity indicates the persistence of the so-called financial “valley of death”. Consequently, co-investment networks, as constructed in this model, encourage as we see risky investments in early stages of the technology life-cycle. Here, relatively small investments might lead to high levels of technological change, given sufficient forecasting capability and investment capacity of the agents. Yet, even heterogeneous networks which connect agents with high forecasting capability with the ones with high endowment are not able to breach the valley of death in technology investments. This leads to the policy implication, that even when harnessing the benefits of co-investment networks to promote technological change, there still remains a need to provide incentives for private investments as well as the provision of public funding in the critical post-lab and pre-commercialization phase.

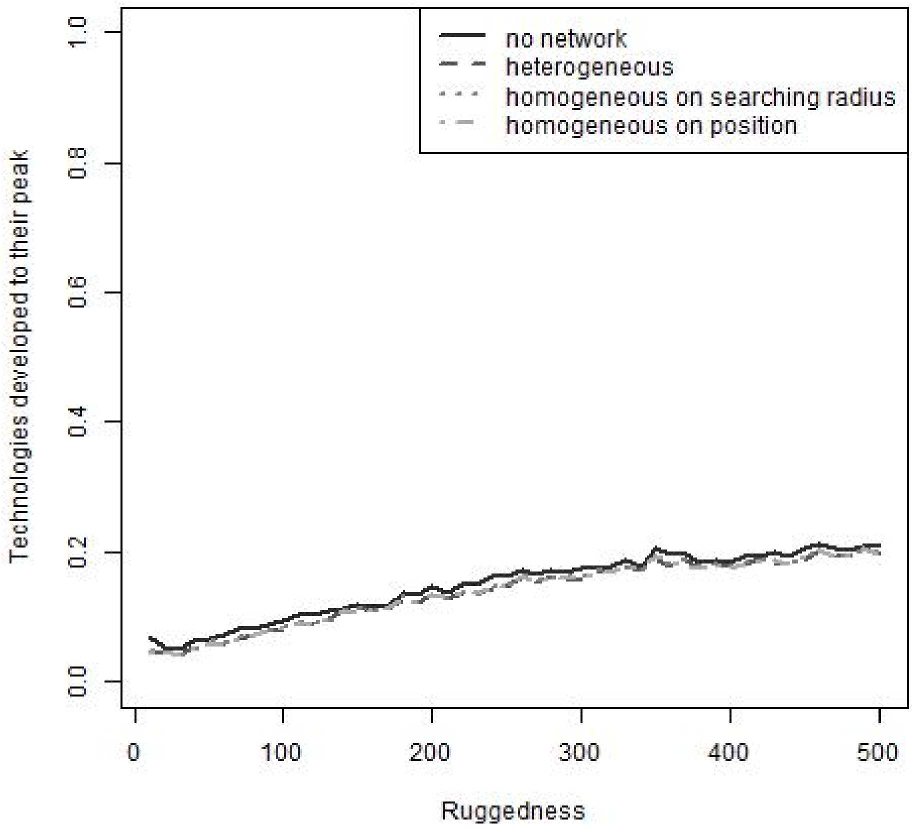


Figure 8: Monte Carlo simulation results on different financial agent networks and technology landscapes - Number of technology peaks discovered

Our overall results indeed indicate networked investor population to outperform isolated investor performance, an effect roughly constant on different levels of complexity of the technology landscape. We also find heterogeneous networks to show a tendency to outperform other more homogeneous network configurations. Both findings appear more pronounced for overall technological change than for the financial agents profits. In line with innovation system literature, these results suggest that in modern complex technological system, heterogeneous networks, appear to be the most conductive environment for innovation to thrive. Yet, even heterogeneous networks

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.

Results from a Monte Carlo simulation indicate networked investor population to outperform the case of isolated stand-alone investors, in terms of investor benefits as well as achieved technological change. Yet, we also find evidence for the existence of a financial "valley of death" - a certain stage in the technology life-cycle where its characteristics discourage further investments, thereby making the technology likely to "die" due to underinvestment. While encouraging investments in early stages, the effect of co-investment networks does not prevent this phenomenon to occur.

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, our results that investment policy conductive for technological change should foremost incentive syndicated rather than isolated investments (as also argued by Avnimelech et al., 2006; Avnimelech and Teubal, 2008). Such initiatives should primarily encourage the teaming-up of investors with heterogeneous resources and capabilities. Yet, even when harnessing the benefits of co-investment networks to promote technological change, there still remains a need to provide incentives for private investments as well as the provision of public funding in the critical post-lab and pre-commercialization phase to avoid potential "valleys of death". Given the availability of sufficient data on investments as well as industry dynamics (as discussed in Christensen and Hain, 2014) 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, 2014), 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.

Compliance with Ethical Standards

The authors declare that they have no conflict of interest.

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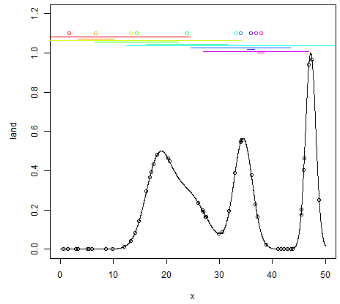
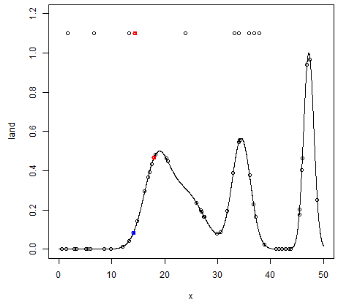
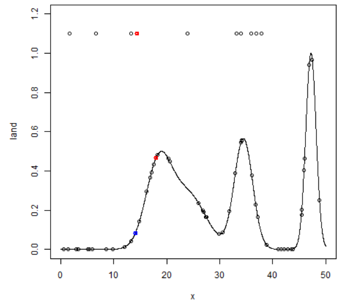
Appendix



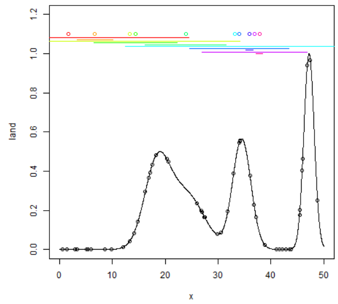
(a) Period 1.0 - Initial Landscape



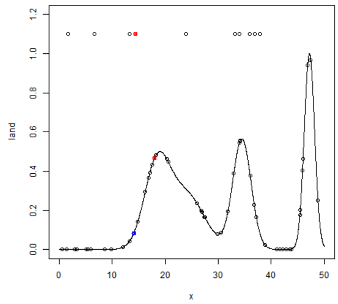
(b) Period 1.1 - Investors exp. Returns



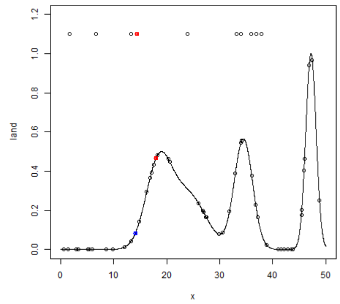
(c) Period 1.2 - Investment choice, repositioning



(d) Period 2.0 - Initial Landscape



(e) Period 2.1 - Investors exp. Returns



(f) Period 2.2 - Investment choice, repositioning

Figure 9: Illustration of a 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.