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A neo-Schumpeterian model of R&D collaboration under technological complexity

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A NEO-SCHUMPETERIAN MODEL OF R&D COLLABORATION UNDER TECHNOLOGICAL COMPLEXITY

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MSc essay of B. Vermeulen (s424850) as generated per 15th June 2007.
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Preface

As far as this essay and my graduation research goes, I thank Bart Verspagen for sacrificing many hours to read my early outlines and drafts to give me advice on the model design, on readability and organization of the essay and on usage of terms and definitions. I thank Han La Poutré for interesting discussions during the exploration phase and comments on how to improve the simulation results during the model design phase. I am particularly grateful for the freedom both Bart and Han gave me in furnishing the conceptual and simulation model. I am glad to have had the opportunity to see Neo-Schumpeterian modeling from up close and I am honored to have been coached by these two aces (no pun intended).
I thank Koen Frenken for several inspiring and helpful discussions and sending me papers. I also thank Koen for enabling me to attend the EMAEE conference. Several models presented there surely gave the inspiration for my own model. I thank Jerry Silverberg and Alessandro Nuvolari for their feedback on early models, Marco Valente for providing me the LSD NK landscape data and an explanation thereof, and Leon Oerlemans for getting me up to date versions of papers.

Browsing through the essay, I realize how much fun it was to do this research. It was tremendously exciting to play around with the various components and definitions in the Neo-Schumpeterian model and to see what kind of behavior emerged. When things got serious in the model design phase, this then was sometimes frustrating. I had to run dozens of simulations for each and every model version in looking for a subregion in the parameter landscape in which our stylized facts might be confirmed. Usually to no avail. As you can read somewhere in the essay, after some degeneracy testing, I all of a sudden realized that part of the emerging behavior is induced by the complexity catastrophe. Since Bart and I selected the Kauffman landscape at the outset, the only thing left for me to do was to convince Bart (and the reader) that the traditional Kauffman landscape has some properties that are not conform our presumptions of what a proper technology landscape is. You bet I am eager to develop a proper technology landscape in the near future.
After this experimentation phase and settling with the operational model, I had to make this loose framework of stylized facts into a proper theoretic framework. Establishing the refined, adorned and synthesized TCE framework was a great challenge. Regretfully, I did not succeed in completely operationalizing it (our operational model was already wrapped up), but we have provided enough clues on how to improve our Neo-Schumpeterian model to overcome that. I am also eager to further study this adorned TCE framework and to improve the operationalizations of the model factors.
The next step was to analyze the simulation results. With some aversion to a strictly verbal assessment of the causes without further obligations, I decided to give the analysis a formal twist. It was great fun to sit back and think of what fundamental mechanisms might be at work, to program a simple test-setting to validate my claims and to eventually come up with some econometric regression model to fit to the data.
You will understand that I am very excited about taking up this interesting PhD assignment!

While wrapping up my essay, I had a look at several other essays of fellow Technology Management students. Most of these essays had a preface with some personal notes. So, let me overcome my embarrassment and also add some personal notes. The milestone of graduation appears to be the occasion par excellence to do so.

First of all, I am grateful for the financial support of my employer GEAR and the profound programming experience I gained over those many years. When I started to work part-time, GEAR allowed me to shift hours freely, which was great, but then again, GEAR never really spared me and gave me full responsibility of serious challenges. Then there was this tyrant CTO that usually did not hesitate to demand my commitment (in this Gordon Ramsey style) to a rush job for a large

customer or pending release. It must however be great to have the authority and financial resources to have the organization turn into interesting technological avenues, to exercise your skills as the technological entrepreneur.
Now that I am about to leave GEAR, I realize that I will very much miss the relaxed, nerdy atmosphere at the B.V. office, the sheer fun with my dear colleagues, the interesting technology and the exciting programming challenges. As far as my graduation goes, I must also thank several of my colleagues for allowing me to use their computers (and even several servers) over the weekend for simulations during this lengthy model design phase. I doubt I will ever have such facilities for simulation at my disposal again!

Despite them being embroiled in their own, complicated lives, I thank my extraordinary mother and brothers for their interest and support throughout the years. Bram, hopefully you are pleased now, now that I finally get 'dat papiertje'. You owe me a beer! Regretfully, my father died gruesomely ten years ago. I had a tough time then and I had to come a long way since. It perhaps sounds a bit sentimental, but getting here feels a bit like a personal victory.

Above all, I am very grateful for having had Rionne by my side for many years now. Rionne, thanks a zillion (I am not sure how many zeros..) for this daily shower of warmth, humor, cosiness and good temper! Hopefully, we will as of now have more time for backpacking in exotic countries, game- and bird-spotting, hike-weekends, city trips, inspiring film-house movies, exquisite dinners with tasty wine, squash and making music together!

By the way, why the heck am I writing this in English? Anyway, it is too late now, I must dash off to the Print Service!

□

Chapter 1

Introduction

In this chapter, we will introduce the reader to the topic of collaboration in Research & Development (R&D), describe what we want to know of R&D collaboration, how we will try to find answers and in what way we narrow down our research. In section 1.1, we will see from recent examples of R&D collaboration as well as conclusions from empirical studies that we still have limited understanding of why and when firms want to collaborate in R&D and as such make deepening of our understanding thereof the research goal for this essay. We will briefly introduce the reader to the basic rationales for the various R&D strategies and the schools of R&D collaboration theories. In section 1.2, we will provide the research specifications. Due to the research instrument we have chosen, we will have to narrow down our conception of various terms, which we will do in section 1.3. In section 1.4, we lay down the structure of the essay, which also provides a good overview of what the research comprises.

1.1 R&D collaboration

There are plenty of examples of collaboration in R&D. Only last February, Organon, the biopharmaceutical/ human healthcare business unit of Akzo Nobel, renowned for developing prescription medicines for gynecology, fertility, neuroscience and anesthesia, popped up in the media for R&D collaboration even twice. The first appearance in the media was on February 14 when Organon and Pharmacopeia, developer of small molecule therapeutics, announced to collaborate in discovery and commercialization of small-molecular therapeutic products across a broad range of indications a.o. neuroscience and immunology. The second time on February 28, because Organon and Acrux, renowned for drug delivery technology, announce to engage in collaboration in the development and commercialization of contraceptives administered through the skin using Acrux' spray technology. Another interesting example is the hunger for collaboration passing through the motherboard and graphics card industry the last few years, with first Leadtex and Foxconn and later Gigabyte and ASUS joining forces in alliances. In February this year, also MicroStar International (MSI), manufacturer of motherboards and actually one of the globally largest hardware producers, announced seeking other Taiwan competitors for a new alliance.
Closer to home, it was only a year ago that Philips announced establishing a joint venture with NEC, the Japanese giant known for its communication systems. The new conglomerate allows NEC to get a foothold in Europe, while it allows Philips to divest and further nurture the somewhat neglected telecommunication technology it does not regard as core competence.
On a personal account, there are also many interesting anecdotes concerning Elektroson B.V., the company from which my current employer GEAR Inc. emerged. Elektroson was at one point in time the world leading recording and premastering software company, with -at its peak- several millions of Dutch guilders revenue a month. The first anecdote concerns an agreement with Software Architects (SAI) dating back to early 1997 on developing an integrated solution to disc image formatting functionality by offering an abstracted interface to the ISO 9660 formatting engine of Elektroson and the UDF formatting engine of SAI. It allowed Elektroson to quickly support the only just established UDF format by simply calling a couple of precisely defined library functions. There was little risk as source code was not revealed and there were well articulated provisions in the contract about using the libraries of the other party. In the meanwhile, the UDF technology was developed in-house and integrated in the existing file system generator. In 1999, the alliance with SAI was broken.
The second story concerns a venturous alliance with Netscape. Over the years 1996 and 1997, the

CEO of Elektroson, Henk Noorderhaven -certainly a technological entrepreneur with vision- pursued in what -in his belief- was going to be the major breakthrough of Elektroson. Elektroson and Netscape would jointly develop a solution to allow users to 'grab the web' and make a backup of websites onto a CD. Due to global dominance of the Navigator browser, Netscape was a tough negotiator and dragged out a good deal. Noorderhaven believed that the webgrabbing would soon start to make Elektroson many millions. What he could not have foreseen was that there were unfavorable market developments and insurmountable technological barriers. First, the Elektroson engineers faced various technical difficulties with incorporating server-side processes. Second, there was a sudden skyrocketing of the market share of the Microsoft Internet Explorer at the expense of the Netscape Navigator, especially after the launch of Windows 98. Last but certainly not least, the product concept, making sites available offline, became commercial inviable by the rise of bandwidth and the steep rise of permanent access to Internet. It was a gamble taken and a gamble lost. Soon the financial resources dwindled, leaving no money for alternative investments, which gave rich American and German competitors the chance to catch up with Elektroson. Early 1998, the once so majestic company went bankrupt and the source code together with key engineers was extracted and put up for sale by American venture capitalists.

From this array of examples it is clear: you only need to scratch the surface to dig up news on R&D collaborations. Although we lack recent figures, Hagedoorn (2002) showed that R&D collaboration is becoming more common in absolute sense in the period from the 60s of last century until the turn of the millennium. He, among others, also points out that collaboration especially occurs in high-tech sectors, with particularly a lot of collaboration in the bio-technology, pharmaceuticals and information technology sectors. He argues that the technology in the high-tech sectors is so complex, that complementary knowledge and skill are more than welcome in overcoming uncertainty of outcome of innovation.
There however are conflicting findings as Dachs et al. (2004) for instance find that R&D collaboration predominantly occurs in medium-tech sectors, although they themselves argue that the national innovation policies play an important role in that. On the other hand, Oerlemans and Meeus (1998) find no sectoral differences and rather argue that collaboration is a widespread phenomenon.
The fact that there are conflicting findings suggests that our current understanding of the phenomenon of R&D collaboration is inadequate, and, more specifically, that the conceptual framework relating technological complexity to R&D collaboration can be improved.
The formal goal of this research then is to increase the understanding of the effects of technological complexity on R&D collaboration. The central hypothesis is that R&D collaboration propensity increases with technological complexity.

In further expanding our understanding of the phenomenon, we can depart from existing basic rationales and theories on R&D collaboration. Let us, first of all, realize that the economic rationale behind R&D is simple: R&D generates technologies and new products which, in turn, generate payoff when sold on the market. We argue that technological conditions limit the set of possible inventions and innovations, while market conditions affect the payoff that can be generated. An entrepreneur is led by its subjective expectations of the future market conditions, developments in technological regime conditions, and own capabilities, and, so, the entrepreneur will pursue a strategy that will yield -given its competences- satisfactory payoff. We can hence argue that the R&D strategy (and hence also the R&D collaboration strategy) is determined by the expectations of market and technological conditions based on subjective perceptions and interpretations. In line with our research subject, the technological complexity determines the R&D strategy, mediated by other technological and market factors.
If we leave the intuition for what it is, we see that the body of literature on R&D collaboration can generally be divided in the field of Strategic Management, Transaction Cost Economics and

the field of Industrial Organization. We will describe these fields in depth later, but they generally differ in their assumptions, their research method, as well as their predictive capabilities. In this essay, we have decided to adopt and adjust the concise and explicit Transaction Cost Economics (TCE) theory (See Williamson, 1985) and introduce several specific Strategic Management findings to directly relate technological complexity to the form of governance of the transaction (exchange of technological knowledge) that is selected by firms. In short, we argue that if technological complexity increases, firms pursue collaboration to seek technologically complementary knowledge, thereby reduce the technological uncertainty allowing them to produce better technology plus generate more payoff and hence give a competitive advantage. The theory also incorporates the fact that, if spillover of knowledge to the collaborating party is large and insufficiently appropriable, firms are likely to refrain from collaborating, especially if competition is fierce.

At the outset of this research, it was opted to design and use a so-called Neo-Schumpeterian model for simulation of an industrial sector. We hereby thus follow the methods emanating from the seminal work of Nelson and Winter (1982) in studying Evolutionary Economics. It was also opted to put the promising Kauffman NK landscape search model to use to operationalize the low-level R&D activity. As we will show, the Kauffman landscape allows, more than other technology landscape models, to immediately operationalize the factors in our conceptual TCE model. By modeling R&D as local search on Kauffman (1993) landscapes (with tunable complexity) on the one hand and endowing agents with collaboration strategies and subjecting them to evolutionary forces by means of endogenous entry and exit (based on search outcome) on the other hand, the effect of technological complexity on emerging collaboration regularities can be studied.
As there is yet a wide variety of technology landscapes in use in Neo-Schumpeterian models, we will however also take this opportunity to evaluate the adequacy of the NK landscape in representing the real search space, the landscape search heuristics in representing R&D activity and, more specifically, whether our operationalizations emanating from the landscape meet the common conceptions. Preliminary simulation studies have indicated that some of the properties of NK landscape and search thereupon are not completely accounted for compared to the TCE and common conceptions.

1.2 Research specifications

Now that we know *what* to research, we need to know *how* to do that and the value of our findings. Here, we will first explain the research design and then the method of data analysis. We will also elaborate on the relevance of this research. It is noted that the direct value of our findings is limited due to our research instrument.

1.2.1 Research design

Recall that we already decided to use simulation as a research instrument. This facilitates a pure experimental research design. We will analyze the data generated in many runs of the Neo-Schumpeterian simulation model in which we systematically vary the input variables. The data on output variables is collected, processed and aggregated to be able to formally address the theoretical hypotheses.
The independent variable is the complexity of the technology of the industry. Complexity will be operationalized as the modularity of technological components, i.e. the Kauffman technology landscape ruggedness variable K.
The collaboration propensity (unit of quality) of the agents in the sector (unit of analysis) is the dependent variable. During each simulation run, the fraction of the projects that is collaborative is registered. These figures are subsequently aggregated in a measure of collaboration propensity.

Our research thus has an experimental character by putting the hypothesis to the test in a simulation setting, but with a strong undertone that we also explore the characteristics of the technology landscape module we plug into the simulation model. As complexity is one of two prime concepts in this research, we will particularly pay attention to possible discrepancies in complexity as operationalized by the NK landscape and the complexity concept as intended in R&D collaboration theories and the implications.

1.2.2 Method of data analysis

As said, the simulation results allow us to formally and statistically address theoretical relationships. We will translate the relationships between factors in the TCE model into causal relationships between operational parameters and output measures. We will also provide parameters in our operational model for the TCE factors intermediating complexity and collaboration propensity. We will use the simulation model to systematically vary the operational parameter for complexity together with the parameter of one of the other variables in the TCE framework. This will allow us to also study the basic interaction effects.

Due to the non-trivial results, we will not simply perform statistical tests, but rather discern the fundamental causes in the operational model that produce the results. We will then establish mathematical terms to describe the behavior of such a fundamental mechanism (i.e. in the form of changes in collaboration propensity due to changes in variables). We will then combine these terms into a non-linear regression model and fit that to the data. We can then of course interpret the coefficients and the goodness of fit. The advantage of this approach is that we also provide a formal justification of the underlying causes rather than a mere verbal explanation without evidence.

1.2.3 Research relevance

R&D collaboration is a central theme in innovation policy, and is seen (by policymakers) as an important way to stimulate innovation in the (Dutch) economy. This project connects this theme to the Neo-Schumpeterian modeling tradition, thereby both promising additional insights into the topic of R&D collaboration, and enhancing the scope of the existing models.
It must however be said that since this research is fundamental and utilizes uncalibrated simulation as research instrument to test theoretic framework assertions, the conclusions are rather qualitative in nature. As such, the immediate relevance of this research is mainly scientific. Appreciative theorizing however supplements existing theories and allows deriving specific hypothesis.
Findings have a limited specific external validity, so if policy instruments are to be engineered to affect the propensity to collaborate, e.g. by adjusting appropriability or introducing standards, one should do so only after rigorous empirical validation in the specific context in which the instruments are to be employed.

1.3 Demarcations and definitions

Here, we will provide demarcations such that the scope of the formulations, claims and findings of our research is clear. The demarcations will primarily concern the type of collaboration and the sectors we address. We will later describe the properties of the sectors we have thus isolated to come to predictions about collaboration propensity using the adorned TCE model we will develop. Furthermore, as we are aiming for a Neo-Schumpeterian model, we will have to narrow down our conception of the industrial sector to be able to formulate an operational model, implement this operational model as a simulation program and later adequately analyze the data and isolate causal chains.
We will also provide context-free operational definitions of the most common concepts (technology,

complexity, spillover). We can then constantly gage the extent to which our use of these concepts in the theoretic treatise of the research subject and the operational model is correct and complete. We will be able to pinpoint the mechanisms at play isolated in the theory by using these definitions. This approach will in the end prove useful, as it also enables us to, e.g., relate the discrepancies between TCE model predictions and simulation results to discrepancies of the context-free complexity and technology concepts and those based on our operational landscape search model.

1.3.1 Limiting of conceptions

Here we will delimit our conceptions of the technological sector and the organizational form we refer to when we talk about R&D collaboration and thereby limit the types of agents operative in the sector.

As mentioned in the introduction, our research will focus on establishing a Neo-Schumpeterian model of agents conducting R&D in an industrial sector, run simulations with that and controlling for technological complexity to get an idea of whether or not the technological complexity invokes collaboration propensity. R&D activity predominantly occurs in *manufacturing* sectors rather than the agricultural and service sectors. In the NACE sector classification, we are then talking about ~~the sectors with codes 15 until and including 37. We can further subdivide these sectors into high-~~ , medium- and low-tech sectors. Typical high-tech sectors are biotechnology, pharmaceutical and information technology. Typical medium-tech sectors are mechanical machinery, motor vehicles and oil refinement. Typical low-tech sectors are food & beverages, textile and printing.
It should be noted that this classification is based on technological *intensity*, and not technological *complexity*. We will see later on that, according to our definition of complexity formulated shortly, the sectors with higher technological intensity have a deeper, more fundamental and more profound use of technological knowledge, which requires the firms involved to conduct more fundamental research as the needed technological knowledge is not generally available. R&D is therefore also technologically more complex. Be aware that there are sectors with technology consisting of more components and spanning more disciplines but where other conditions (like standards and interface agreements) narrow R&D down and hence make R&D easier. We therefore feel comfortable to associate the technological intensity with technological complexity of R&D. In subsection 2.3.2, we provide a more elaborate treatment of this association.

Let us first indicate what kind of organizational form of knowledge exchange we will label as 'R&D collaboration' and then further specify the structure of the sector we will model.
Firstly, there are numerous inter-organizational interactions and congregations in which technological knowledge is exchanged. If a firm is purposefully looking for new technological knowledge, it can decide to -rather than conduct R&D in-house- seek for external sources (see e.g. Chiesa, 2000, for an elaborate overview of such sources) to gain more technological understanding. It is common to pursue an acquisition or merger, or establish a research joint venture. Less rigorous methods are to fund R&D activities at another institute or company or completely outsource R&D activities.
In this essay, emphasis is less on the formal organizational form in which such exchange of technological knowledge occurs, but rather on the implications of the attuning of (operational) R&D tasks. We are interested in whether and -if so- how organizations should best share technological knowledge and research capabilities. In this sense, technology alliances and consortia, technology networks and joint R&D organizational forms are closer to the type of R&D collaboration we claim to investigate. R&D collaboration is henceforth taken to be based on relatively formal agreements taking (loose) contractually established forms concerning the configuration of conjoint R&D efforts of two independent economic agents.
We however have to specify this even further. An economic agent can collaborate horizontally, i.e. with (potential) competitors possibly operating in a geographically different market, as well

as vertically, i.e. with agents operating up- or downstream in the value chain. An agent can also collaborate with public institutes or across sectoral boundaries. Here, we will however focus on horizontal collaboration between firms in the same, private sector, possibly with different disciplines and fields of expertise, but all targeting the same market. There are no other agents in the sector, so the population of agents is homogeneous.

1.3.2 Definitions and descriptions

We will now provide a description of technology, a decomposition of the concept of complexity into five dimensions and a description of the leaking of knowledge due to R&D and R&D collaboration.

First of all, technology is the specification for a product and how to produce that product and provide service for it, and how to put it onto the market (even including a prescription for sales and marketing decisions like price and output quantity). As we will see, this 'comprehensive' definition is especially useful to allow us to limit the operational model as we then do not need to specify and introduce these activities in our operational model. Operationally, we conceive technology as a hierarchy of components consisting of elements, where elements are functionally interrelated, both within the same component as well as across component boundaries. As we will see, this low-level conception of technology is closely related to the actual codification of technology.
As such, R&D is conceived as the process of generating technologies (invention) and improving those (innovation). So, technology is the yield of invention and innovation activities. Innovation is commonly metaphorically modeled as search on the technology landscape, while invention is then modeled as picking a point on the landscape to start searching from. In line with our low-level conception of technology, invention is generating a specification of the set of elements to use, while innovation is a structured process of adjusting elements and components or even adjusting the architecture of components to improve the performance of the whole.

Second of all, let us specify the concept of complexity. With in the back of our head that we are working toward a complexity concept allowing us to use the (NK) technology landscape, we will start off from complexity as conceived in the application of complexity theory to product development (See Frenken, 2001). In this view, "complexity stems from interdependencies between different elements in a technological artefact". From the technology landscape definition of performance of technology ('fitness'), we see that this performance in fact is perceived as the average performance of the constituting elements. These elements however interact through a web of technological interdependencies thereby affecting the performance of one another. Technology is said to be complex if the effect on overall performance of the technology of each of the elements is affected by the choice for many other elements. Technology is said to be modular or simple if the effect on overall performance of the technology of each of the elements is predominantly determined by the performance of that single element in isolation.
Singh (1997), drawing on authors like Simon (1969), Henderson & Clark (1990), Holland & Miller (1991), takes this definition one step further and defines complex technology as "an applied system whose [elements] have multiple interactions and constitute a nondecomposable whole". Largely in line with the previous conception, Singh argues that technology is a hierarchy of components consisting of technological elements, where the performance of each component depends on the performance of its elements, while (possibly intricate) interactions of elements, possibly across component boundaries, together determine the performance of the whole. The crucial departure from the NK technology landscape definition of complexity is the non-decomposability. Singh follows Holland & Miller (1991) and Perrow (1994) in arguing that random changes in components (of properly functioning technology) are likely to interfere functioning of other components through the intricate web of interactions and are thereby likely to seriously degrade the performance of the whole. Singh takes it even one step further and argues that the function of a unique combination

of elements and their interactions within a complex technology are hard to reproduce with other combinations and configurations, and follows Teece (1986) in that the various elements and components are therefore strongly complementary and co-specialized.

When it comes to R&D of technology, we can immediately add two more dimensions to technological complexity. Firstly, we follow Marsili (1999) in arguing that the heterogeneity of the knowledge base required for R&D also adds to the level of complexity. If knowledge and capabilities required for effective R&D are spread across various disciplines, its integration to realize an innovation is hard and complex. Secondly, we argue that the maturity or specificity of the knowledge base also is a dimension of complexity. If technological knowledge is generally available and standardized, the technological elements might be intricately related, but the technology search space can be aggregated due to which technological complexity does not manifest itself during R&D. We hereby meet the notion that complexity also relates to specificity of the technological knowledge. This specificity relates to the efforts required to discover particular knowledge. If the technology is mature, a fair deal of the technological knowledge is expected to be generally available.

We now have a technological complexity concept comprising five dimensions: the intricacy (as an expression of the number of elements and the number of interconnections), the hierarchy of components (and, possibly, the distribution thereof over disciplines), the (non-)decomposability of the whole technology, the diversity of disciplines (or, if you like, differentiation of the knowledge base) and, finally, the specificity or maturity of the technology.

Please note that the narrow (NK) technology landscape definition is only concerned with the first dimension, while the first three dimensions allow for a more generic description on technology. The last two dimensions of technological complexity are richer in that they closely relate to the technological regime and sector conditions.

Third of all, let us explain what spillover and externalities are. We will later see that spillover and externalities play an important role in explaining the collaboration propensity. Upon conducting R&D, part of the knowledge that is required to produce the technology is embodied in the technology itself. Once this technology is brought to the market, other firms can imitate and reverse engineer the technology. Part of the knowledge that originates from the first producer thereby 'leaks' to other parties. This type of generic, undirected spillover of knowledge is referred to as 'externalities'. Upon conducting R&D with another party or having an outside party conduct R&D through outsourcing, part of the knowledge that is required to come to feasible technology is conveyed to that other party. Sometimes this only concerns specification of the interface, but often also some more sensitive information concerning the internal functioning of the technology is disclosed to allow for more freedom in designing the complementing components and thereby coming to better solutions. This other party hence gains more knowledge of the technology than would by ordinary externalities. We will refer to this as (directed) outgoing spillover.

Clearly, if a firm does not conduct R&D, this firm does not leak knowledge, not in externalities, not in directed spillover. If a firm does conduct R&D internally, it will suffer externalities from knowledge embodied in the technology, but not directed outgoing spillover. If a firm does conduct R&D and either outsources part of the R&D to a third party or either collaborates in R&D with a third party, it will suffer (but also enjoy) both spillover and externalities. The level of spillover however differs, as firms are more reluctant to share knowledge with a party to which they only outsource R&D than to share knowledge with an intimately known collaborator.

We will furthermore distinguish non-adherent and adherent spillover/ externalities. Adherent spillover/ externality concerns innovation engineering knowledge that can be applied more generally and brings about an increase in innovation efficiency of the receiver for future activities. Non-adherent spillover/ externality concerns information on specific technological parts that is only of value for the technology being discussed. The effects of spillover are limited to cost savings in the present context. Adherent externalities are relatively rare, but profound reverse engineering research might also reveal the processes by which the technology being analyzed was realized.

1.4 Structure of the essay

This essay is geared toward establishing a Neo-Schumpeterian model in which R&D collaboration can emerge, where R&D is modeled as search on an NK technology landscape in which we can control for landscape complexity. We will however not bluntly establish an operational model based on crude assumptions, but carefully graft our operationalizations on the existing theories and following the example of existing models, hereby abiding by the methodology of simulation modeling.
In chapter 2, we introduce the reader to the theoretic side that will allow us to come to a conceptual framework that will be operationalized. Since we need an economic theory that provides an explanation why firms conduct R&D, we will first introduce the general, mainstream theories and their account of technological change. We will see that picking the Evolutionary Economic theory is quite self-evident if we want to -like us- have an endogenous mechanism for technological change and innovation. In following the Evolutionary Economic (EE) theory, we acknowledge non-linearities and intricate interactions of economic actors and are obliged to establish a Neo-Schumpeterian simulation model to investigate our research questions experimentally. Taking the Evolutionary Economic behavioral premises as a starting point we review the various schools of thought on R&D *collaboration.* Since we are particularly interested in establishing a simulation model as externally valid as possible, we have decided to pick the Transaction Cost Economic (TCE) theory as a starting point, as it is concise and comprehensive and allows us to derive specific predictions. We signaled that there are shortcomings in the theory and decided to refine and patch the model with specific theories and concepts derived from the body of Strategic Management theories. We will show that our thus established adorned TCE model can indeed be used to assess the state of affairs in various manufacturing sectors and derive predictions about the overall R&D collaboration propensity.
In chapter 3, we provide a survey of the simulation models of R&D and R&D collaboration. We will see that there are comprehensive models of R&D as well as more fundamental models and that we are more interested in the more fundamental models so as to be able to transparently disentangle cause-and-effect in our experimentally obtained findings. As these fundamental models often are hardly more than basic applications of search on so-called technology landscape search, we will provide a classification of technology landscapes and provide a short overview of the classes. We will then account for our choice of the NK technology landscape to model R&D in our Neo-Schumpeterian model.
In chapter 4, we will discuss the methodology of simulation and simulation model building. It primarily concerns the stepwise translation of our conceptual model, via operationalization into a quantified, parameterized simulation model, hereby trying to maximize the various types of validity. We implicitly follow the methodology to arrive at our simulation model (so we will not constantly refer to the methodology), but we will shortly evaluate the internal validity after having formulated the operational model. We will also use the methods provided in guiding our simulation trials and take the notions concerning the external validity in account when formulating our conclusions.
Given the ingredients of the method to follow, clear examples of how a Neo-Schumpeterian model looks like, a pre-selected technology landscape search model, clear premises for the economic agents and finally a firm conceptual TCE model to implement, we formulate the operational model in chapter 5. As the very core of the operational simulation model is the NK landscape search model, we elaborate on that, but also hint on the limitations on internal validity we thereby introduce. We furthermore introduce the evolutionary framework by means of a market for deselection of agents and a mechanism for entry and imitation of strategy for novelty. We then provide operationalizations of the relationships discerned in the conceptual TCE model formulated as hypotheses.
In chapter 6, we present the results obtained by using the simulation model obtained by implementing the operational model. As should be clear from the chapter on methodology we have to

limit ourselves to a part of the parameter landscape and have to justify our choices. We present the simulation results and provide explanations for them. Since the results are difficult to comprehend, we have decided to search for fundamental causes rather than resorting to just the usual verbal account of the phenomena observed. To do so, we inspect the properties of the various components of our operational model and subsequently show that formulation of econometric terms reflecting these fundamental mechanisms yields regression models with a decent fit to the data. Due to the limited resources and due to the fact that the most important results (on complexity and collaboration complementarity) contradict our main hypothesis, we discarded a fully-fledged robustness analysis of the model.

The results obtained are certainly interesting and we are able to draw interesting conclusions in chapter 7. We have alarming conclusions for NK landscape devotees as both our main hypothesis and the external validity of the NK landscape are disputed. We elaborate on the issues concerning the technology landscape, as it is so important in the field of Neo-Schumpeterian model. Despite these issues with the technology landscape, we are able to hark back to the TCE model and enlighten the reader on some of the claims postulated there. Eventually, we will formulate some recommendations for improvements and for follow-up studies en provide the fellow-student with some tips to be taken at heart when designing a Neo-Schumpeterian model.

Chapter 2

Theory of R&D and R&D collaboration

In this research, we study how conditions in the industry and more particularly characteristics of the technology of that industry affect the R&D collaboration propensity. To do so, we have to understand what makes an individual firm conduct R&D.
The first question (which one would expect to be naive) that springs to mind is: why and when would a firm conduct R&D? At the fundamental level, economists quarrel over the nature of the phenomenon. The mainstream Neo-Classical Economics camp argues R&D is an abnormality and that there is no urge (endogenous to the industry to which a firm belongs) to improve either the product or the process. The heterodox Evolutionary Economics camp argues that R&D is at the core of firm behavior while a firm its dynamic efficiency determines its very survival. Since we need a theory with an explanation of when agents will conduct R&D, it is obvious we will adopt the Evolutionary Economic theory as our fundamental framework. We will however provide a proper introduction to Evolutionary Economics (and the dispute with Neo-Classical Economics) and thus shed light on the rational for firms to conduct R&D in section 2.1.

As we will see, the Evolutionary Economic theory (EE) argues that firms conduct R&D to withstand competition of each other and that thereby the population composition, the strategies and goals pursued and technological conditions change. Current formal methods are inadequate to formulate broad Evolutionary Economic models, so to cope with the conceptual complexity and dynamic intricacies, Evolutionary Economists usually resort to computer simulation to study operational models of their specific theories. We will introduce the reader to the specific class of Neo-Schumpeterian models in section 2.2.

The next question that springs to mind is: why and when would any firm conduct R&D *in collaboration*? Despite the fact that EE provides a rational for R&D and thereby an explanation for industrial dynamics, many specific phenomena related to R&D still need specific theories (which are of course grafted onto the behavioral premises of EE). Also for collaboration of firms in R&D we need a specific theory. In section 2.3 we will discuss three different strands of specific theory on R&D collaboration and come to a partial synthesis of two of them to form a conceptual model that explains when and why firms are willing to conduct R&D in collaboration. Eventually we will use the factors in that conceptual model to pinpoint the sector differences to explain the collaboration propensity.

2.1 Economic theory on technological change: Evolutionary Economics

As hinted in the introduction, we will consider only two fundamental economic theories in trying to explain R&D. It is not our intention to reiterate the many arguments pro and contra either the Evolutionary Economic or the Neo-Classical Economic theories, but we do want to pinpoint why R&D does not occur in one theory but does in the other. As we will see, the difference lies in the basic assumptions of the theories. Subsequently, we will describe the basics of Evolutionary Economics.

In the traditional Neo-Classical Theory of the Firm (See e.g. Oerlemans, 1996; Verspagen, 1991), there is a set of fundamental assumptions that allow us to derive that there is no such thing as endogenous innovation. Three assumptions concern characteristics of the economic agent (the firm): an economic agent is *perfectly rational*, an agent is *profit maximizing* and an agent is *perfectly informed* of prices, performances and techniques. Three assumptions concern the characteristics of

the market. Agents produce the same homogeneous good and operate on a spot-market with many suppliers and many customers and there are no costs involved in transaction of an acquired product or switching to an alternative supplier. There are no governance forms other than unilateral coordination through the market, i.e. firms either produce it or buy it from the market.
As all agents (including customers) are profit maximizing (and therefore cost minimizing), a lowering of price would attract *all* customers (given that there are no switching and transaction costs). As such, all other manufacturers will follow by setting the same price to recapture customers (the theory however does not explain what would make customers return). As agents are profit-maximizing and cost-minimizing they are thus inclined to simply adopt the most efficient process technology around and set the price and quantities produced to maximize profit. This brings about an equilibrium price that allows manufacturers to cover operating costs but that there is no excess profit.
The same line of reasoning holds for a change in (production) techniques. First of all, note that a change in techniques that forces a manufacturer to raise the price would make that manufacturer lose all of its customers and hence such a process innovation will not pursued. A change in techniques that enables a manufacturer to lower the price would attract all customers. Competing manufacturers will have to follow (in order not to perish) and implement the same alternative techniques to be able to set the same price. Note that competing manufacturers can actually also do that because they have perfect information on what techniques the competitors use and are fully capable of using those techniques. So, cost reducing process innovation would lead to instant imitation by other manufacturers. There is no single incentive to innovate and agents simply pick the production techniques already on the shelf that minimizes marginal costs. We end up in a situation in which all firms charge the same price (equal to the marginal costs) and use all the same or equivalent production techniques.
Product improvement would bring a manufacturer into a different market in which it again has to choose the production techniques and the prices that would yield as much profit as possible.

Neo-Classical economists have tried to ameliorate the existing framework to incorporate technological change. Verspagen (1991) contains a survey of 'new' Neo-Classical models (e.g. Romer, 1986; Lucas, 1988) that claim to endogenize innovation by including it as a production factor. The approach in those models is to plug the production factor into an external, publicly available knowledge base. Technological changes by one firm however immediately spill over to the external base from where all competing firms put it to use. As such, there is no micro-level incentive for firms to conduct R&D as costs of investments cannot be recovered. In alternative models that try to overcome that (e.g. Aghion and Howitt, 1990; Romer, 1990; Grossman & Helpman, 1989, 1990, 1991) a second, 'research' sector is introduced. This sector produces blueprints of new goods as input for the first sector and general technological knowledge as by-product. In order to introduce a micro-level incentive for producers of blueprints to actually research new and better blueprints, these firms can patent blueprints which allows them to enjoy monopolistic profits.

Neo-Classical models in general fail to explain technological change following from conditions of the sector and fail to provide micro-level incentives to engage in R&D. On the one hand, in traditional models, only an *exogenous* disturbance or technological change (whatever the source can be) will force manufacturers to reassess the current situation. If the technical change concerns process techniques, all manufacturers will instantly revaluate all techniques available and if necessary acquire an alternative process technology from the market, put it to use perfectly and adjust prices so as to withstand competitors (that are doing exactly the same).
On the other hand, the new Neo-Classical models rely on a 'trick' of introducing a second sector (hence, the change is still external to the principal sector) and for that the models even need to breach several traditional assumptions (perfect information - knowledge is no longer a pure externality and markets are no longer purely competitive).
Clearly, individual firms in the principal sector will not conduct R&D as they cannot cover the

costs of it, as there is no capital available to invest (there is no excess profit) and as competitors immediately imitate the technology perfectly, the price advantage is enjoyed only for an infinitely small period in time.

In clear contrast to this Neo-Classical Theory of the Firm, there is Evolutionary Economics that provides robust endogenous explanations of technological change. Evolutionary Economics strongly opposes the Neo-Classical assumptions. First of all, EE rejects the ideas that an economic agent is perfectly rational, is fully informed and is only profit maximizing. Theories in Evolutionary Economics typically are based on boundedly rational, imperfectly informed and satisficing economic agents.
In this theory, firms themselves perpetuate technological change within the industry by the felt necessity to anticipate innovation by competitors. So, rather than a reaction to exogenous disturbances, innovation is a deliberate attempt of a firm to improve its market position. Innovation thereby forces other firms to follow or anticipate in order not to lose the battle over customers. In line with the bounded rationality of economic agents, innovation certainly is not simply a matter of acquiring the appropriate technology at the market to implement what is required to optimize the product or production process. Innovation rather is a painstaking process of trial-and-error, gradually shaping ideas of in which direction to search while other firms in the field constantly displace the target.
It exactly are these uncertainties and limited individual capabilities involved in developing technology which make it (sometimes) economically sound to combine knowledge and share risks with other firms.

As said, we need a framework that allows for endogenous mechanisms inducing R&D. From the introduction is should be clear that Evolutionary Economics is more suitable than is Neo-Classical Economics. We will now elaborate on the premises of Evolutionary Economics. The theories in Evolutionary Economics are build on three key pillars (See Frenken, 2005, citing Andersen, 1994):

- Schumpeterian concepts of innovation and industrial dynamics
- Simonian ideas of bounded rationality
- Alchian's ideas of the market as a selection device

Let us shortly describe those three concepts.

Firstly, Schumpeter provided a framework in which he demystifies (fully fledged) industrial dynamics[1]. Schumpeter argues that booms within the economic realm "consist in the carrying out of innovations in the industrial and commercial organism" (See p.295 Schumpeter, 1927). He certainly is not interested in incremental improvements but particularly in "changes in methods of production and transportation, or in changes in industrial organization, or in the production of a new article, or in the opening up of new markets, or of new sources of material". Schumpeter continues to argue that in perfect competition, 'newcomers' cannot cover the 'interests' of borrowing capital. If this 'newcomer' would however be able to establish 'new combinations', he would be able to not only cover the capital and interest, but also, as long as competition does not catch up, make an additional profit.
Schumpeter then makes plausible that innovation thus may yield competitive market power[2]. Although Evolutionary Economists now work with more materialized and crystallized theories, we can already see the outlines of what is now know as typically Schumpeterian[3] concepts of technological

1. At the time, Schumpeter was interested in developing a theory explaining the so-called business cycles. Schumpeter was looking for an *endogenous* driver of the cyclical phenomena that could be discerned empirically (See Schumpeter, 1927). In doing so, he developed the foundations for a framework that is used nowadays to explain industrial dynamics.
2. Although we would now feel comfortable with concepts of market forces, Schumpeter is inclined to 'prove' the power of the parties involved by translating differences between firms in inequalities in capital and purchasing power.
3. For the record, Fagerberg (2002, p.7) stipulates that Schumpeter was heavily influenced by Marx' idea of techno-

change. Firms innovate to consolidate their position and to withstand and defy competitors. Firms anticipate and react to strategic moves from competitors, therefore innovate and thereby shape the mutual environment. Successful innovation, extraordinary growth and the accompanying high concentration draws 'swarms' of imitators entering the industry, which in turn causes slowdown and vanishing profit margins. As such, Schumpeter's framework can also be seen as a first attempt to formulate a theory of the industry life cycle. The bottom-line is that by endogenizing innovation in economic theories, we can explain industrial dynamics and economic growth.

Secondly, Simon (1955) rejects the perfect rationality of humans in decision-making. Simon argues that there is paradox related to the research subject of the Neo-Classical theory of the firm. The problems of the internal structure of a firm would actually not be there if the human decision-making would be really rational as is axiomatically assumed. A perfectly rational man would after all know how to perfectly organize its firm and hence there is no theory of the firm required. Substituting "a choosing organism of limited knowledge and ability" for the rational "economic man" would lift the paradox. In a nutshell, Simon (1955, see p.102 for the formal definitions) shows that humans perceive only part of the behavioral alternatives, can only to a limited extent comprehend and hence forecast the outcome of actions and cannot estimate the true payoff if the outcome is to actually occur. Evolutionary Economists argue that these Simonian capability constraints can be extended to the behavior and capabilities of firms.

Thirdly, Alchian (1950) argues that markets are selection devices. Alchian's idea starts off from the notion of Knight that "entrepreneurs decide what the firm will do rather than have the market dictate the activities of the firm" (See Boudreaux and Holcombe, 1989, p.153). As this entrepreneur faces uncertainty and there are risks involved, there is no such thing as profit maximizing. Alchian argues that various types of firms (mutations) have different probabilities of survival (natural selection) and argues that due to natural selection, a particular type of firm is more probable to emerge (See Alchian, 1950, p.220). Typically, inefficient firms are "weeded out" (Boudreaux and Holcombe, 1989). An implication would hence be that even without omitting uncertainty and incomplete foresight, surviving entrepreneurial practices at least are relatively efficient -or, more far fetched, even profit 'maximizing'- given the economic circumstances. Nooteboom (2006, p.6) stipulates that this often is a usual argument behind the assumption of 'efficient outcomes', but that Winter (1964) already showed that this is a weak argument. It is not necessarily the best firm possible, but rather the best firm available in the population that survives. Nooteboom furthermore points out that efficient selection is hampered by presence of monopolies, entry barriers and transaction costs.

The three pillars of Evolutionary Economics hence span a generic framework in which industrial dynamics is explained from innovation urged by limited capabilities and evolutionary deselection. Firms have an imperfect, subjective representation of their environment and are not able to accurately forecast yields of innovation efforts. This is due to imperfect knowledge and limited cognitive capabilities, but also because the future is unknown and yet to be shaped in non-linear interaction. Firms hence are engaged in a process of searching for competitive advantage, guided by an imperfect representation of a constantly changing environment and employing imperfect innovation practices. Some firms' innovation routines fail, forcing them into demise, while routines employed by others prove superior causing the firms to flourish. This in turn causes their products and strategies to be imitated and improved.

This ongoing process of propagation strategies and accumulation of technologies by imitation, mutation in the form of innovation being imperfect technological change and selection by the market based on the innovation performance is the research subject of the field of Evolutionary Economics (EE).

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logical competition between firms. Schumpeter however extended the notion of innovation from purely mechanizing (to render labor obsolete) to product improvement, new input resources and even new ways of organizing.

2.2 Neo-Schumpeterian models

The dynamics emerging from evolving, non-linear, interactive micro-level behavior will yield severe complications in treating Evolutionary Economics in a formal manner (e.g. a mathematical model). Although some authors devised non-linear econometric models with endogenous non-linear drivers of dynamics (see Goodwin, 1951, w.r.t dynamics at macro-economic level), it became apparent that the mathematical methods to solve or treat (and perhaps even formulate) this type of models are not (yet) suitable to cope with the need for heterogeneity of a dynamic set of agents and complex behavioral heuristics. The intractability of complex, evolutionary and non-linear processes makes such an exact approach impracticable if not inadequate or even impossible (c.f. Pyka and Fagiolo, 2005).

With the rapid development of computers in the 60s and 70s, simulation methods started to come into use in various sciences. It was for Nelson & Winter (See Nelson and Winter, 1982; Andersen et al., 1996) to first use simulation techniques to study industrial dynamics by having an array of 'agents' operate within an economic environment, with each following its own heuristics given its unique qualities. In the 25 years since those Nelson & Winter models, a vast number of such -since these models are designed to shed light on the research topic of and hereby following the general ideas of Schumpeter- Neo-Schumpeterian models. Although these models abide by the three aforementioned dimensions, i.e. Schumpeterian innovation driving industrial dynamics, Simonian capability restrictions and Alchian selection into account, it was, and, actually, it currently still is, necessary to implement fair abstractions of the Evolutionary Economic theoretic framework. It is noted that there are numerous classifications of Neo-Schumpeterian models (See e.g. Windrum, 2005; Dawid, 2005; Frenken, 2005; Kwasnicki, 2001, Cowan, 2004; Silverberg, 2003), but this is not the place to come to a comprehensive synthesis.

Let us now elaborate on the idea behind such Neo-Schumpeterian models. These models have a population of micro-level (software) agents operating within a model of the economic environment and are metaphoric models of a (non-specific) real-world economic industrial sector. An agent represents an individual firm (or rather the entrepreneur) and there generally is no meso- or macro-level authority or external driver. The model is geared toward having industrial dynamics really emerge bottom-up from interactions of the agents. To meet Simonian restriction, those agents typically follow simplistic heuristics to determine their (re)actions. These heuristics do not only help the agent to deal with its environment, but -since Neo-Schumpeterian models actually focus on technological change- will also focus on 'searching new technologies'. These technologies yield payoff depending on the competitive performance of those technologies. By introducing costs of 'R&D', on the one hand, and payoff for technologies (depending on some uncertain appreciation/ object function), on the other, agents can be deselected based on their dynamic efficiency. To establish Schumpeterian dynamics, it should also be possible for agents to enter the system and to imitate technologies. By having Alchian selection and Schumpeterian threat of entry and imitation, an evolutionary framework is established. We will now elaborate on how Neo-Schumpeterian models incorporate the following four key ingredients:

- Constellation of micro-level agents
- Agent heuristics
- Evolutionary framework
- Schumpeterian innovation and industrial dynamics

2.2.1 Constellation of micro-level agents as metaphor

Based on the *use* of agent-based models, we can, grosso modo, distinguish two classes: agent-based models as a metaphor used to study real-world phenomena and agent-based models for industrial

applications.
The earlier type of models represents an existing real-world ecology (read: society, economy, community, production system) of entities, whereas the latter type can, in addition, also supplement[4] existing real-world ecologies which then become 'agent-aided'. Excellent examples of the agent-based models of the latter category are (see Van Dyke, 1998) the XEROX market-based climate control system, the Zone Logic transfer line monitoring and the Metra DAEWOO press shop scheduling system.

The class of Neo-Schumpeterian models is a (small) subclass of the earlier class of models. The agents in Neo-Schumpeterian models represent firms and although these agents are usually functionally equivalent (homogeneous), they can be heterogeneous in their beliefs and heuristics. It is well possible to introduce agents that represent other types of institutions, e.g. customers, banks or governmental organizations, but as there are yet still so much fundamental issues unresolved, those 'auxiliary' agents are rarely introduced and even demand is usually aggregated in a single payoff function.
It is crucial to realize that the Neo-Schumpeterian economist is primarily interested in meso- or macro-level regularities that emerge from non-linear interactions of micro-level agents. Neo-Schumpeterian economists generally have agents follow simplistic heuristics rooted micro-economics rather than have 'intelligent' agents ('intelligent' in the sense of Wooldridge, 1998). This then meets Simonian capacity restrictions and furthermore facilitates discerning the exact causal chains. Not only do Neo-Schumpeterian agents follow simplistic heuristics, they also tend to have a limited notion of the environment in which they operate. The agents therefore often have limited notions of the market they serve and limited models of other agents.

2.2.2 Entrepreneurial heuristics

The agent model can take various forms, ranging from being nothing more than a set of parameters for which generic formulas are applied, a string of elements of technology landscape for which a single function is executed and a comprehensive object with own technology repositories and unique history based beliefs about other agents and the economic reality they operate in.
Given the comprehensiveness of the agent model in a Neo-Schumpeterian model, we distinguish two sets of heuristics:

- the R&D heuristics relating to the very core of the Neo-Schumpeterian models, i.e. technological change
- and the complementary heuristics to cope with the economic environment in which the agent operates

Drawing from the body of Neo-Classical models, early Neo-Schumpeterian models rely on the latter type of heuristics and -quite surprisingly- underexpose the actual R&D and innovation process. Frenken (2005, p.8) also observes this: "[The early models] are almost exclusively focused on competition between firms with different technologies, rather than with technological development as such". Recent fundamental models seem to rather simplify the environment heuristics and elaborate on the R&D heuristics.

Firstly, we will discuss the R&D heuristics. The R&D concept comprises both the actual R&D strategy (in terms of what to pursue) and the operational level innovation activities. Both should reflect the fact that the firms suffer bounded rationality, limited knowledge and imperfect foresight,

4. A philosophical note: applying agent-based systems might even change economic premises, e.g. introducing automatic bargaining/ negotiation systems (c.f. the models La Poutré is working on) to handle otherwise (too) costly micro-interactions, brings about increases in strategic and operative efficiency which in turn defies Simonian 'satisficing'.

which in fact is convenient for modeling and computer implementations rather than problematic, as these Simonian restrictions allow us to introduce proxies and simplistic heuristics.

The strategic level R&D heuristics often simply determine whether to imitate or innovate, whether to collaborate or to work solo, and -if the agent decides to collaborate-, whether it will free-ride or will engage actively. The strategic level R&D heuristics often also encompasses the R&D investment strategies (invest how much in what).
Some authors argued to make the R&D strategy more realistic, e.g. by having the amount invest by an agent dependent on the income of last periods (e.g. Silverberg & Verspagen), or by having the agent improve its investment strategy periodically in terms of changing the heuristic parameters through genetic programming (Yildizoglu, 2001) or a training neural network (Yildizoglu, 2003).

The operational level R&D heuristics, i.e. innovation model, is conceived metaphorically as search on a technology landscape. In order to reflect the limited foresight, bounded rationality and imperfect information, the outcome of innovation is uncertain. In some models this causes innovation to be likely to lead to poor optima, while in other models, e.g. those of Nelson & Winter, the improvement is Gaussian distributed around 0. Imitation often boils down to making an (imperfect) copy of the technology of another agent. Innovation often commences from the current or a random location on the technology landscape and then simply executes the operational steps described later on. Collaboration does take the form of e.g. exchanges of technology or information or consecutively recombining outcomes of operational innovation steps.
An elaborate treatise on landscape search models can be found in section 3.2.

Secondly, we will discuss the complementary 'organization heuristics'. In the Nelson & Winter model, these organization heuristics determined the price and quantity to produce. An aggregated demand market would subsequently disburse payoff.
Nowadays, comprehensive, applied models certainly incorporate such decisions, e.g. through a Cournot game, but more fundamental models omit explicit, comprehensive organization heuristics. It is simply assumed such decisions are implicitly codified in the technology representation. The performance or fitness of technology then immediately yields a proportional payoff.
In Neo-Schumpeterian model, such 'organization heuristics' are used to introduce interaction between and interfacing with other agents.

2.2.3 Market as evolutionary selection device

We will now describe how the concept of 'evolution' comes into play by starting with a short treatise of the original (Darwinian) concept of evolution. We will then pinpoint the discrepancies with the evolution concept in economic context. Next, we will shortly discuss the way the evolutionary framework of novelty, variety and selection is currently implemented in Neo-Schumpeterian models, which in fact is a rather narrow implementation of the economic concept of evolution.

Charles Darwin's notion of evolution is based on natural selection. If an individual has a mutation which makes it better adjusted to the given circumstances (e.g. scarcity of resources, subjection to predation of some kind, emerging preference for particular sexual features, et cetera) than his non-mutated fellows of the same species, this individual is less likely to succumb and is more likely to spawn offspring. It thereby propagates its mutated genes (genotype) reflecting in its mutated features (phenotype). Through an ongoing directed accumulation of mutations, the species as a whole gradually adapts to the circumstances.
For this 'adaptation' mechanism to work, there must be different mutations competing (for food, survival under predation or mating) such that there is sufficient progress in development and there must be an influx of mutations such that the pool of mutations does not dry out.

There is no integral translation of the evolution concept in the realm of economics.

Apparently Schumpeter was quite wary to use -if not repudiating- the term 'evolution' in his writings and to some extent rightfully so. Evolution in economics is certainly different from that in (genetic) biology. There are three main points to be made:
Firstly, there is an apparently old argument that firms actually are able to 'acquire and propagate traits' (e.g. through imitation and passing it on onto a spin-off), so the device of change is not purely mutation at the very conception or production (i.e. startup). As such, the economic evolution concept here resembles that of Jean-Baptiste Lamarck (1744-1829) more than that of Charles Darwin.
Secondly, evolution can be described as 'population-level learning': only the population as a whole gradually adapts to the circumstances. In reality, an entrepreneur also learns of its mistakes thereby readjusting its routines and strategy repertoire. A firm also mutates by means of innovation of its routines. This 'firm-level learning' should ideally also be taken into account.
Thirdly, the accumulation of advantages appears to be more prominent in economics than is in the animal kingdom. Apart from age, physical development and perhaps social hierarchies, two individuals situated in the same region face in essence the same conditions. The competition of two individuals is thus relatively fair which makes the exerted natural selection force relatively strong and pivotal on the mutation, at least much stronger than is the market selection force. Two firms can also differ in a great many other features (size, available capital stock, expertise, brand loyalty et cetera), some of which are related to time of entry or the way the firm came about (spin-off, diversification, new startup) and has developed (lock-in, sunk costs, path dependent beliefs et cetera). Firms can furthermore specialize on niches or target multiple markets thereby spreading risks and allowing cross-subsidization. This matter constitutes a scientific field of its own.

That said, we have to acknowledge that many of the Neo-Schumpeterian models devised so far still abide by the evolutionary framework spanned by the three key concept of 'Darwinian' evolution (Windrum, 1999):

- novelty/ mutation
- selection
- variety

The converse is certainly not true: many economic simulation models utilize some flavor of evolution but are certainly not Neo-Schumpeterian. A clear example is the use of evolutionary genetic programming, which is used for optimization, and is often used to detect 'locally optimal' heuristics for (not necessarily rational) agents to follow (See e.g. Alkemade, 2004; Tesfatsion, 1998). Many of the models in close adjacency with Neo-Schumpeterian models either violate the actual Schumpeterian premises of endogenous entry and exit, Dosi / Nelson & Winter single instance trajectory deployment or the Simonian restrictions, and some furthermore not even concern innovation and its driving of dynamics!
Let us now elaborate on how each of those factors is implemented in *genuine* Neo-Schumpeterian models and with a brief stipulation of the Evolutionary Economic conceptions or real-world manifestations thereof.

Firstly, let us look at the concept of novelty. In Darwinian evolution, the source of novelty is (genetic) mutation at conception / production. Mutation gives an individual the distinct features that make it a novel candidate. In Evolutionary Economics, the source of novelty is innovation and (imperfect) imitation of strategies. Neo-Schumpeterian models in turn limit this concept of novelty even further in two ways.
The first point is that evolution exerts pressure on R&D strategies through the performance of these R&D strategies. Novelty does refer to mutations of R&D strategies and *not* to its output, i.e. innovation, which is the *mean to deselect* R&D strategies from the population! This certainly is a narrow interpretation of the Schumpeterian concept of innovation. Prominent Evolutionary Economists like Schumpeter, Nelson & Winter and Dosi see new ways to organize R&D certainly

also as innovation and also as output of R&D. There hence is no double-loop learning in Neo-Schumpeterian models.
The second point is that novel strategies usually are only introduced *by entrants* that either start with a fresh (random) strategy, or by (imperfectly) mimicking[5] a superiorly performing agent. If the model relies on entry to be the only source of novelty, the adaptation is at population-level, not at the firm-level. Firm-level learning is only occasionally implemented (see e.g. Yildizoglu, 2001, 2003).

Not only is the novelty concept limited, also the engine behind novelty is different. In the real-world economy, firms enter an industry or pursue innovation because entrepreneurs believe there "might be something profitable out there" (e.g. favorable market conditions, own technological discoveries) and thereby bring about self-sustaining growth patterns (Fagiolo and Dosi, 2003). A Neo-Schumpeterian agent has no internal 'motivation' to enter stemming from a belief that something profitable will turn up from R&D. The Neo-Schumpeterian model has some criterion to determine when an agent enters, so this (endogenous) entry mechanism does have this belief enclosed. In the Nelson and Winter (1982) model, a set of potential imitative and innovative entrants is maintained and one of those agents actual enters if the *estimated* net income from production exceeds a predefined threshold.

~~Secondly, let us look at the concept of selection. In Darwinian evolution, natural selection refers~~ to the survival of the fittest, but also through chances of propagation of genes due to (emerging) preferences, i.e. sexual selection. In Evolutionary Economics, bankruptcy and deliberate exit, and imitation of superior agents and spin-offs (and imitation of technology!) are the evident analogies of selection and propagation, however dwindling returns obviously force an entrepreneur to adjust strategies, to completely reorganize or even to hand over the control to someone else. So, due to such firm-level learning, poor performance does not automatically entail demise, and hence the mechanism of selection is certainly not as crude as the Darwinian counterpart.
In comprehensive Neo-Schumpeterian models, the outcome of R&D strategies, i.e. innovations, is used to deselect strategies from the population. So, the technological achievements at least facilitate ordinal ranking of strategies. Some endogenous rationales would then have to bring about exit of low ranked inferior strategies. Nelson & Winter for instance have a firm exit if the performance, in terms of marginal profit per unit capital, is below a critical level.
Many Neo-Schumpeterian models simply follow the trivial approach to have the agent bear certain expenses for R&D search, while innovations/ technologies yield payoff to cover those expenses. A 'successful' R&D strategy would then obviously generate relatively much profit, while an 'unsuccessful' strategy would yield losses and, if this persists, eventually cause bankruptcy.
Propagation and novelty actually are closely related. Entry does not just introduce novelty, but entry also propagates part of the qualities of the agent being imitated. As superior agents are imitated more, their R&D strategies spread more.

Thirdly, variety is driven by novelty. Unlike in ecologies, where there is co-evolution of different species and natural circumstances, or in real-world economies, where there are disturbances and technology shocks in adjacent industries, Neo-Schumpeterian models often have an economic reality (in which the agents operate) which does not contain such external events or drives. It certainly is possible that a co-evolutionary force makes the system end up in a relatively static or cyclical peaceful coexistence of firms (but not necessarily a static population). So, in Neo-Schumpeterian models, variety is certainly not persisting per se.

Theoretically, novelty will cause the population of strategies to be sufficiently varied. Therefore, there is sufficient competition of those various mutations, which will fuel deselection of inferior strategies and hence drive the process of adaptation. If however imitation is the most prominent

5. This imperfect imitation does also do justice to the Simonian capability restrictions.

source of novelty (which in fact is the case in most Neo-Schumpeterian models), there usually is a transient onset-phase during which inferior strategies exit and a stable, 'ergodic' phase in which one or multiple co-existing strategies dominate(s). So, if the source of novelty is not random, but path-dependent, variety is decreasing.

2.2.4 Schumpeterian innovation and industrial dynamics

Nelson & Winter can easily be excused to have restricted their models to Marx' technological competition manifesting itself in process innovation as these models are the very first attempts of a Neo-Schumpeterian simulation model. Schumpeter however had a comprehensive innovation concept in which innovation not only concerned Marxian production process improvement, but firms would also improve their product to reposition themselves on the market, would even seek new strategies. Only few modern so-called Neo-Schumpeterian models actually do explicitly focus on product innovation, e.g. Gerybadze (1982) and Kwasnicki (1992), let alone renewed types of organizing (See Kwasnicki, 2001).
It however must be said that most technology landscape codifications can well have technology instances represent both production process, product and service characteristics, and even strategies and firm features. So, the technology concept not necessarily prescribes what is being modeled and the technology concept does allow studying Schumpeterian innovation. Then again, we already saw that Neo-Schumpeterian models do not feature entrepreneur/firm-level learning by means of adjustment of heuristic parameters, let alone the heuristics themselves. These firms in these models also do not gradually improve their understanding of the technology landscape they are operating on, let alone double-loop learning.

As most Neo-Schumpeterian models feature endogenous entry and exit, allow for head starts, lock-in, path-dependencies and mere coincidences play a significant role in (or rather is intrinsically intertwined with) the development of an industry, these models meet the notions of gradual deployment of an industry crystallizing in a single trajectory of a multitude of possible trajectories. If the criteria of exit and entry are appropriate, and if an entrant can (imperfectly) imitate technologies already developed, then there is a progression of the technology frontier.

2.3 Economic theory on R&D collaboration: Adorned Transaction Cost Economics

As we already argued, the Evolutionary Economic theory is par excellence the framework suitable to explain the propensity to engage in R&D. We are thus looking for a specific theory that is reconcilable with the premises of the Evolutionary Economic framework and is geared toward explaining R&D *collaboration.* As a consequence, the theory must have economic actors that suffer bounded rationality and imperfect information, and that collaboration is a mean to overcome the uncertainties related to development of the industry and surrounding the outcome of R&D activities. The specific theory of R&D collaboration[6] we are looking for must therefore comprise an explanation of when firms are likely to collaborate by assessing the (what that theory deems) magnitude of positive contributions of collaboration and weighing these with the unfavorable conditions. As hinted in the introduction, we expect this to be a combination of technological and market factors.

If we now look at empirical findings, we get an idea of what our theory should incorporate. Kleinknecht et al. (1991) concluded from their survey that firms collaborate in R&D because it increases innovation efficiency by sharing resources, (financial) risks, knowledge and competences

6. Recall from the demarcations in section 1.3, we will limit our discussion to collaboration between private, commercial firms targeting the same market. Hereby we thus excluded relationships in which either one or both of the parties is (are) non-commercial or public (e.g. a subsidized research institute).

and has constituents benefit from economies of scale and scope. Firms then pursue R&D collaboration if these advantages appear to or are expected to outweigh the disadvantages of spillover, opportunistic behavior and sharing payoff. Other empirical studies have indicated that the motives for collaboration are, on the one hand -related to R&D-, the technological complexity and the uncertain and costly nature of research, and, on the other hand -unrelated to R&D-, access to the market and the search for opportunities (Bayona et al., 2001; Sakakibara, 2002; Hagedoorn, 1993). We thus expect a theoretic framework that allows (immediate) prediction of the R&D collaboration propensity from the necessity to overcome uncertainties, the means to reap benefits from sharing qualities (i.e. competences, knowledge, resources, capabilities, access) and the means to overcome the circumstantial disadvantages and the adverse effects of sharing those qualities.
There are -grosso modo- three complementary strands of theory about formal research partnerships: the Strategic Management theory, the Industrial Organization theory and the Transaction Cost Economic (TCE) theory (See Hagedoorn et al., 2000, p.570). We will shortly discuss these three strands and provide argumentation for picking the TCE framework.

The Strategic Management (SM) theory is broad but generally studies the strategy for a firm to follow to overcome market and technological uncertainties. Thereby, collaboration is thought to improve the comparative competitive position by providing firms access to complementary resources ~~(Teece, 1986). Collaboration also allows firms to focus on core competences and even expand the~~ effective scope of own activities (Porter, 1986). Collaboration thereby also reduces the costs of having to rely on the market for specific arrangements and reduces the costs of having to enter alternative markets. Some go as far as arguing that collaboration is a vehicle for organizational learning (Hamel & Prahalad, 1989) and to, thereby, enter new technological areas (Dodgson, 1991). SM provides many specific theories concerning the effects of R&D collaboration, but does not have an integrated framework that allows us to predict when firms are inclined to collaborate.

Industrial Organization (IO) theory studies strategic behavior of firms and the effects on the industry. So far, the models of R&D collaboration in IO are mathematical and have game theoretic aspects (See e.g. Hinloopen, 2000; Cellini and Lambertini, 2005; D'Aspremont and Jacquemin, 1988). Although these models allow integration of concepts like imperfect appropriability and cost-reducing R&D, the industry is often reduced to a duopoly and firms are often conceptually limited by blunt assumptions like 'firms do optimal investments'. This severely impairs the external validity and obviously violates the Evolutionary Economic presumptions. Formal approaches do not (yet) allow elaborate treatment of conceptually rich models and inclusion of Simonian restrictions, path-dependencies and emergence of regularities from complex, non-linear multi-agent interactions. Another crucial shortcoming of IO theory is, as far as our conceptual framework concerns, immediately related to what is concluded by Hinloopen (2000, p.174) in his paper: "proper treatment of uncertainty in models of strategic R&D is still lacking".

Transaction Cost Economics (TCE) actually regards an economic exchange (transaction) as the basic unit of analysis and focuses on explaining the governance structure in which this transaction is organized. The idea is that a boundedly rational actor -Knight's (1965) notion of "human nature as we know it" (See Williamson, 1981, p.549)- selects a governance form (internal, market or a hybrid form like in collaboration) to minimize costs of this transaction (Williamson, 1985). The TCE framework facilitates predicting the governance form based on the transaction costs as determined by the characteristics of the transaction. These characteristics are the level of (behavioral) uncertainty surrounding the transaction, the frequency with which this transaction occurs and the specificity of the investments required. In TCE, uncertainty primarily concerns not (exactly) knowing how the market will develop under influence of actions by competitors and/ or technological developments. We see that TCE meets the behavioral presumptions of EE and it allows immediate prediction of the governance form from a concise theory.

In picking a theoretic framework, we exclude IO for obvious reasons and we are left with the choice between the smörgåsbord of Strategic Management theories and the relatively coherent Transaction Cost Economics theory. A clear advantage of using TCE rather than SM is the quantity of input (an assessment of only a few factors) required to come to a recommendation and the type of recommendation (immediately the governance form that is (to be) pursued - exactly what we want). In employing SM, the researcher will need a range of qualifications of the industry, the firm(s) and the technology concerned to derive a set of strategic action alternatives.
If we now perceive an R&D venture requiring exchange or rather transactions of knowledge, we see that we can immediately use TCE to predict whether an R&D venture is outsourced, conducted in-house or undertaken in a technology alliance from an assessment of the three aforementioned factors (frequency of interaction, specificity of investments and the behavioral uncertainty involved). A clear advantage of using the TCE framework over using the SM theoretic framework is its conciseness and that the prediction is based on boldly clear-cut and simple factors of the exchange itself.
Add to this that the TCE framework can be expanded painlessly: various authors -including the most prominent exponent, Williamson itself- have demonstrated that the TCE framework can be extended with concepts borrowed from Strategic Management theory. Sometimes factors from Strategic Management theory are introduced as operationalizations of (the relatively abstract) TCE concepts (See e.g. Brockhoff, 1992), sometimes these factors are introduced as additional concept in the TCE framework (See e.g. Nooteboom, 2006).

So, we clearly select the TCE framework as a starting point. During exploration of the TCE literature, we noticed that some authors criticize TCE concepts and some authors find that the predictions done by TCE are sometimes outright incorrect. In subsection 2.3.1, we will ameliorate the TCE framework by refining the concepts and integrating SM factors and argue that this framework tackles the outstanding criticisms.
As we are interested in explaining the differences in collaboration propensity in different types of manufacturing sectors, we will employ the thus developed TCE model in subsection 2.3.2 to assess these sectors and to thus derive prediction concerning the collaboration propensity in these sectors.

2.3.1 Theoretic conceptual framework

As said, we will first reduce the readily introduced TCE framework using the (obvious) properties of R&D collaboration ventures. We will then propose a refinement of the uncertainty definition and subsequently show that a couple of the most vexing objections to the uncertainty concept in the traditional TCE framework are resolved. Next, we will provide disaggregate factors for each of the uncertainty concepts and thereby wrap up the introduction. The thus established framework and its constituting factors will then be described in more detail. We will -on a per factor basis-pay attention to the relationship with the operational definitions provided section 1.3, appreciative theory from empirical findings as well as the SM theories to prop suppositions on the effects of the factor. Eventually we will provide a short integrated view on the framework as a whole and thereby stipulate some additional interactions of the factors.

Reduction based on properties of R&D

We have decided to adopt the TCE framework but to reduce it to the form relevant for R&D collaboration. We feel, like several other authors like Nooteboom, Hagedoorn and Oerlemans, well comfortable with seeing 'exchange of knowledge' also as transaction. The transaction costs in fact are formed by establishing a formal arrangement for the frequent exchange of knowledge constituting R&D, hereby contractually safeguarding against (behavioral) uncertainty (at least, according to the traditional TCE framework - we will expand on this in subsequent paragraphs), especially if asset specificity is high.

In figure 2.1, we find the table from which we can read the recommended (and also probably most occurring) governance form based on the frequency (vertical dimension) and the asset specificity (horizontal dimension) of the transaction if behavioral uncertainty is at a medium level. We see that the more specific the assets and investments become and/ or the more frequent the transaction occurs, the less external the preferred governance form becomes. If investments are generic, a firm best buys the technology on the market based on a contract with little obligations as it is then easy and also not detrimental to take business elsewhere (e.g. upon opportunistic behavior). If investments are becoming more specific, a firm needs more certainty that the transaction takes place properly as breaking up is more costly, and is hence inclined to either do it itself or tie the executing party through more tight bilateral or trilateral contracts with more and more explicitly formulated obligations.

	Investment characteristics		
Frequency	Nonspecific	Mixed	Idiosyncratic
Occasional	Market governance	Neoclassical contracting	
Recurrent	Classical contracting	Bilateral governance	Unified governance

Figure 2.1: Williamson's table of the preferred governance form by asset specificity and frequency of interaction. Our assumptions lead us to conclude that the governance form preferred *for R&D* is in one of the two cells demarcated.

R&D of course is a special type of economic transaction. A genuine innovation process requires researchers to constantly reshape their image of the technology they are developing based on constantly discovered insights. We argue that the frequency of interaction is at least not low. We would otherwise talk about outsourcing development in the face of a clearly specified design rather than conducting R&D that is after all surrounded with a certain level of technological uncertainty. We however expect the exact frequency of interaction to depend a.o. on the complexity of the project itself and the underlying knowledge base.
We also argue that although the investments required for R&D always have some specific character, some of the knowledge that is generated can be applied more generally than others. Asset specificity hence depends on the characteristics of the knowledge base and specificity of applications of the generated knowledge. We will come to discuss this later when further expanding our notion of a.o. *complexity*.
So, we assume that R&D concerns relatively frequent, reoccurring transactions requiring specific investments for at least a certain part of the R&D project. If we follow the original TCE framework and fill out these properties of the transaction (exchange of technological knowledge in an R&D project), we see that if the uncertainty is moderate, we end up in a situation in which the most suitable form of governance is either 'unified' or 'bilateral' (depending on the specificity of investments), i.e. either internalized or in collaboration (See Williamson, 1985, p.79). We see that in figure 2.1, we end up in either one of the two demarcated cells. If behavioral uncertainty however is high, it becomes increasingly hard to cover possible 'contractual holes'. Bilateral governance is then departed for either market or unified governance (See Oerlemans, 1996, p.75 on Berger, 1990).

Refinement of uncertainty concept

We just sketched the TCE framework applied to governance of R&D. This framework now has several shortcomings that we will discuss briefly. In order to do so efficiently (and to ameliorate the TCE framework), we will now first redefine uncertainty to comprise of three dimensions (where all have firm-level and industry-level components):

1. Technological uncertainty. In conducting R&D, firms do not know ex ante what technology to develop, not how to develop particular technology and to what extent innovation will be successful.
2. Market uncertainty. The market preferences are insufficiently enunciated. Customers do not know ex ante what they want. Firms do not know what other firms are up to.
3. Behavioral uncertainty. A collaborator may be opportunistic and free-ride efforts or put spillover to own use. We also aggregate behavioral uncertainty to include the use of externalities.

We will now evaluate the most prominent criticisms and show that they vanish in the light of this refined uncertainty.

Firstly, Williamson's conception of uncertainty is purely behavioral in nature and the implications are too clear-cut. Many authors (e.g. Oerlemans, 1996; Faems et al., 2004; Nooteboom, 2006) dispute the prominent role of opportunism. In Faems et al. (2004), this is taken one step further. The authors start off by pointing out that TCE prescribes establishing a detailed contract to safeguard oneself against opportunism. Next, they stress that doing so would limit 'explorative' R&D in its inherently uncertain path through the technology landscape. Firms will not go beyond what is allowed in the contract. They conclude this is a paradox: if firms want to conduct R&D collaboratively, they would have to formalize it to prevent opportunism, a formalized governance however hampers effective R&D. TCE thus underestimates the role of trust and 'mutual hostage' situations (Nooteboom, 2006). It is therefore argued that also 'soft' contracts with 'holes' do not necessarily predict a departure for unilateral R&D in the presence of (some level of) behavioral uncertainty.

Secondly, during the development of an industry, we argue that the various types of uncertainty develop differently. Since the original TCE framework lacks (industrial) dynamics, such considerations are missing. Ordinarily, the specifications of what to produce and how to do that are only gradually crystallizing under influence of the emerging intrinsic, underlying properties of the technology and the choices of the various parties in the industry. During development of an industry, there is a path-dependent, increasingly specific image of what customers want, what the firms offer and how they should produce what the customer wants. With the gradual development, the degrees of freedom decrease, firms and customers become increasingly dedicated to a particular paradigm and find themselves locked in. So, technological uncertainty and the demand-side of market uncertainty decrease. During the take off of the crystallization of the market and technology, the (financial) risk of entry decreases which attracts other and more manufacturers. Firms are then supposedly more tempted to be opportunistic and to copy (well-defined) technologies to facilitate quick entry of the still attractive and the by now well-demarcated market. So, we argue that while technological and market uncertainty diminishes, behavioral uncertainty rather temporarily peaks.

Thirdly, TCE predicts unilateral governance if there is high uncertainty. This is in contradiction with empirical findings that for high levels of technological and market uncertainty, there actually is *more* R&D collaboration (Lundvall, 1990; Nooteboom, 2006)! Lundvall (1990) argues firms are reluctant to integrate, as they would loose flexibility and opportunities to learn by precluding working together with other firms. Nooteboom (2006, p.13) comes to similar conclusions: "greater uncertainty in an industry, in terms of the volatility of technology and markets, yields a greater need to engage in outside relations with other organizations, to correct for the myopia of organizational focus".

However, given the understanding we just gained (in the previous paragraph) that the different

dimensions of uncertainty develop differently over the development of the life-cycle, let us recapitulate the alleged contradiction found by Lundvall and Nooteboom. As we see it now, this really is based on a misconception of the concept of uncertainty. Technological and market uncertainty gets firms to collaborate for complementary (technological and market) knowledge and (technical and marketing) competences. Collaboration is also pursued to overcome financial risks if the market develops and reacts differently than expected. *This* is found by Lundvall and Nooteboom. Upon emergence of the technology paradigm and dominant design, entrants and competition are eager to collaborate in order to reap the effects of spillover. This brings about an increase in behavioral uncertainty, which in turn discourages R&D collaboration. *This* is meant by Williamson.
We see that if we abandon the static nature of the original TCE framework and use the framework in an exposition of the dynamics in an industry that the considerations in determining the governance form no longer just depend on behavioral uncertainty, but we also need to take into account the technological and market uncertainty. We also see that we then indeed tackle the major outstanding critique. We will now discuss the factors that actually determine those forms of uncertainty.

Factors determining uncertainty

~~We have thus first reduced the TCE framework based on the frequency and asset specificity of~~ R&D and next refined the TCE framework to predict collaboration propensity from a multidimensional uncertainty factor. We will now specify the disaggregate factors that actually determine these forms of uncertainty, but -given that we aim for a Neo-Schumpeterian model (with near-homogeneous agents)- we opt for introduction of several industry-level factors and hereby exclude firm-level factors[7].
R&D collaboration is in fact pursued to overcome the technological uncertainty related to how to make whatever is to be made (demanded by the market). A prominent variable in determining '*how* to make' something is of course technological complexity. In line with the subject of this research, we will introduce this technological complexity into the model. Empirical findings (See Hagedoorn, 2002; Dachs et al., 2004; Hagedoorn, 2003; Bayona et al., 2001) have indicated that technological complexity explains a great deal of variance in collaboration propensity, but it is insufficiently accounted for in the theoretic framework.
Market uncertainty concerns '*what* to make' and closely relates to the development of consumer preferences as well as the moves by competitors shaping the demand characteristics. In order not to over-complicate the model, we assume that if consumer preferences get more clear (a dominant design emerges), that competition rises and (more crudely) that high levels of competition refers to multiple players targeting the same niche hence indicating consumer preferences are more clear. As done in the second remark on the uncertainty concept, these market uncertainty factors can be conveniently used in a dynamic exposition of the adorned TCE model.
Behavioral uncertainty concerns what collaborators do with spillover. Several authors (Cassiman and Veugelers, 2002b,a; López, 2004; Sakakibara, 2002) observed a strongly mediating role of appropriability of R&D efforts in determining whether firms are willing to collaborate. Williamson himself also introduced appropriability as far as acquisition of cost-saving innovation is concerned, but did not properly integrate it in his theory (See Oerlemans, 1996, p.76-79).
We thus have complexity determining technological uncertainty, the level of competition functioning as a proxy for market uncertainty and appropriability determining the behavioral uncertainty.

If we now zoom out to the strategy level, we see that -given that the frequency of interaction is not low, and that asset specificity is not low- our adorned TCE framework predicts the propensity to collaborate (in terms of the probability of preferring bilateral hybrid over hierarchical governance)

7. For an overview of firm- and industry-level factors, see Sakakibara (2002)

from the transaction costs. This decision in fact is made based on a cost-benefit analysis for both types of governance (and possibly for alternative collaboration candidates). On the cost side, for collaboration, the principal firm incurs costs for the Nooteboom three C's (contact, contract, control), while for working solo, the firm incurs costs for internalizing particular technological knowledge so as to be able to the same R&D. On the benefit side, the advantages are strongly related to the actual motives aforementioned (See e.g. Kleinknecht et al., 1991; Hagedoorn, 1993). Obviously, benefits relate to the adequacy of internalization, which in turn depend on complementarity of the knowledge targeted and the current knowledge base, and the eventual efficiency of conducting R&D.
We hence see that complementarity of knowledge bases and complexity both strongly determine the transaction costs and the probability that internalization will succeed. As the underlying dimensions of complexity (see section 1.3) determine the specificity of the assets and the frequency of interaction, complexity as such strongly determines the governance form preferred. We also see that the level of appropriability relates to the magnitude of the Nooteboom costs. Competition furthermore puts pressure on (dynamic) performance of all parties, stresses efficiency in either internalizing or collaborating, and further amplifies the role of appropriability.

For history sake, we will occasionally use the notion of transaction costs, but, for convenience sake, we generally reason from the contribution of a collaborator vis-à-vis working solo. To go short, the value of collaboration in terms of increases in performance (or dynamic efficiency) is affected by the extent to which the partner actual contributes *complementary* knowledge in overcoming technological uncertainty, given the project characteristics largely induced by technological complexity, and the extent to which the constituting parties can appropriate the returns of their respective contributions.

We have thus obtained the outlines for an adorned TCE framework for R&D, predicting the collaboration propensity based on complexity, appropriability, competition and complementarity. We will now discuss each of the four factors, by providing a definition or description (possibly closely related to the operational definitions provided in 1.3), evaluating the empirical evidence or theory on the subject and elaborating on the role of the factor in the adorned TCE framework for R&D. Eventually we will shortly evaluate the whole framework.

Complexity

We have just seen that complexity strongly relates to the uncertainty on how to make something that is required. Empirical research has indicated that collaboration propensity increases with complexity (See Hagedoorn, 2002; Dachs et al., 2004; Hagedoorn, 2003; Bayona et al., 2001; Singh, 1997). We will now show how technological complexity fits within our framework. We will first zoom in on the operational level to show that -arguing from our technological complexity definition (provided in section 1.3)- collaboration contributes to overcoming problems in improving technology in R&D. We will then zoom out to the strategic level and show that the TCE framework predicts that firms collaborate.

Focusing on the dimensions of complexity at an operational level given in section 1.3, we immediately see that if collaborators have different fields of expertise (i.e. the know-how concerning components in the technology), involving them would reduce technological uncertainty. As R&D often concerns combining a multitude of disciplines, collaboration might be beneficial. Collaborators (possibly) contribute expertise on adjacent disciplines, are thereby able to consult on interfacing to complementary components (to keep performance of particular components at an acceptable level while adjusting others), and to (at least more efficiently) assess feasibility of suggested designs or propose designs for these complementary components. The additional know-how is increasingly valuable if the technology is strongly non-decomposable, since collaborators signal incompatibilities

sooner and thereby increase efficiency. Efficiency arguments will increase if the relationship between the various components (and elements within) become more intricate and less standardized and when the knowledge that is targeted with R&D is more specific (less generic) and less disclosed (by e.g. fundamental research).
We see that, reasoning from operational benefits, ceteris paribus, collaboration is more desirable if technological complexity is relatively high than if it is relatively low.

Focusing on the motives at a *strategic* level, we see that, given that technological uncertainty rises with technology complexity, we can provide a rationale within the traditional TCE line of reasoning that argues collaboration is *statically* efficient and we can provide a rationale within the adorned TCE line of reasoning that argues collaboration is *dynamically* efficient.
First of all, transaction costs are high due to the increasing information asymmetry (See Bayona et al., 2001, on Robertson & Gatignon, 1998) and hence the increasing number of potential 'contractual holes' that are to be covered (See Oerlemans, 1996, on Berger, 1990), while, on the other hand, internalization costs are high due to the specific knowledge that is required (Singh, 1997). So, since both market and hierarchical governance are expensive, the alternative of hybrid governance is more attractive (Singh, 1997). Collaboration hence is statically efficient.
Second of all, if the technological complexity is high, and the development of the technology trajectory is erratic, transaction costs are preferred over lock-in and sunk costs. Firms prefer to remain flexible and want to be able to change supplier and/or customer to select other input materials and component technology (Lundvall, 1990). Especially if technology is relatively complex, firms seek appropriate (temporary) partners for complementary knowledge to bridge gaps in the knowledge base. Outsourcing would preclude wandering off in particular technological avenues (Faems et al., 2004) and internalization would yield a lock-in and sunk costs. Collaboration hence is dynamically efficient.
We find more support for the claim that collaboration is efficient by reverting to the operational definition of complexity. We see that if complexity predominantly concerns inherent intricacies, that interaction becomes more frequent if complexity increases as tuning of one component to other components (in other disciplines) becomes more crucial as incompatibilities are more likely to rise. If complexity is, furthermore, characterized by high specificity of knowledge or application, then the technological knowledge is not generally available, which makes internalization costly and collaboration with sources of complementary knowledge even more interesting.
So, with higher frequency of interaction (related to relevant technological intricacy), the preferred governance form shifts from market governance closer to internalization, while the high costs of internalization shifts the preferred governance form from internalization to market governance. We see that these forces counterbalance and make collaboration even the more likely.

So, we now see that in the face of high technological complexity, collaboration is both operationally and strategically likely. In the following subsections, it will become apparent that the other factors in the TCE framework however still mediate.

Appropriability

As commonly known, appropriability concerns the degree to which the returns of efforts can be captured. Appropriability particularly relates to possible use of spillover and/ or externalities (and hence related to behavioral uncertainty). It is an empirical fact that only if firms can sufficiently protect their proprietary information, they are willing to engage in collaboration (Cassiman and Veugelers, 2002b,a; López, 2004). We will first elaborate on the concept of appropriability in the context of R&D and R&D collaboration at an operational level. We will then evaluate the concept of appropriability in the context of the TCE framework. Eventually we will discuss the advances of our adorned TCE framework over the original TCE framework.

Firstly, let us look at what appropriability is and how it affects R&D and R&D collaboration propensity. Recall the operational definition of spillover and externalities provided in section 1.3. From that description we understand that although R&D might materialize in products of which the returns can be reaped easily, part of the knowledge and know-how embodied in the technology 'leaks' to other parties who can then use it to their own benefit without having had to invest in producing the knowledge in the first place. As such, externalities and spillovers thus form a disincentive to conduct R&D (Katz, 1986).
From our operational definition of spillover and externalities, it also became clear that the type and extent of leaking technological knowledge also depends on the governance form chosen. In case of unilateral governance, the firm only suffers externalities. In case of outsourcing, the firm in addition to externalities also suffers spillover, but limited to interface specifications and perhaps some basic understanding of the internal working of components so as to come to decently performing complementary components. Such spillover often is non-adherent since the chance is small that the receiving firm can use such knowledge in other occasions than purely this single R&D project. In case of bilateral governance, the intention is to establish cross-fertilization or synergistic performance increases. A selection of the knowledge concerning the technological connection of elements internal to the various components hence is shared to come to new interface specifications (or even alternative component boundaries) that allow departure of the current design for better performing components and a better performing system. It hence involves -to some extent- showing the internal working of the components that have technological interdependencies. Such spillover is said to be adherent if the receiving firm can use such innovation engineering knowledge in other occasions than purely this single R&D project. This would allow the receiving party to further research technology given the newly developed interface, but also diversifying R&D into developing the component on which it just received information. As competitively sensitive information might be put to use by the collaborator, the relative performance and dynamic efficiency of the firm(s) involved will change.
Appropriability instruments have been devised to allow capturing returns from R&D efforts (either in the form of the product or the technological know-how accumulated) and thereby restore the incentive to engage in R&D and even R&D collaboration. There are grosso modo three ways to appropriate. Firstly, prevent knowledge from being leaked simply by not disclosing information on the internal workings (e.g. secrecy, gray-box co-development). Secondly, prevent knowledge, if leaked, to be put to (opportunistic) use by claiming the right on the use of a particular configuration of elements (e.g. patenting, explicit contractual arrangements and otherwise protecting intellectual property). Thirdly, rely on lead-time advantages by being the first to market and hence assuring that 'monopolistic profits' can be earned until competitors have caught up with the technology (e.g. design secrecy, design complexity, trade secrets). It is generally easier to appropriate the returns from a particular configuration of elements (this can, after all, be patented) than the engineering knowledge required to come to technology. Due to its low inherent appropriability, asymmetric outgoing adherent spillover generally is a disincentive to collaborate.

Secondly, let us review the role of these appropriation instruments within the TCE framework. Since we are focusing on predicting when firms will collaborate, we will focus in appropriation instruments of the second kind, i.e. those that prevent putting outgoing knowledge to use. *Appropriability* then refers to the degree to which these instruments are available and effective. We will now first review the conceptual role of appropriability in the TCE framework. We will then assess the effect of appropriability on the governance form likely to be chosen. After that, we will discuss some alternative views of appropriability.
First of all, we have decided to expand the TCE model with the concept of appropriability predominantly for two reasons: it refines the behavioral uncertainty factor and it refines the decision for a governance form. The first reason is trivial as appropriation instruments make putting knowledge

to opportunistic use ineffective. The second reason is more complicated. Appropriation instruments supplement contracts and bring down costs of covering contractual holes and costs of control. By bringing the transaction costs of collaborating (and outsourcing) down vis-à-vis the transaction costs for internalizing the knowledge required for similar innovation potential, choosing for an alternative governance form becomes attractive.

Second of all, now that we understand that appropriation instruments decrease transaction costs for externalizing, we will refine our look on the governance form to be chosen.

The degree to which firms externalize R&D strongly depends on the level of appropriability. If knowledge is perfectly appropriable, other conditions completely determine whether R&D is outsourced, conducted in collaboration or internalized. If knowledge is unappropriable, a firm will be inclined to internalize knowledge required for innovation. Only if complementarity is high and own performance severely inadequate a firm will seek external sources.

In reality, the level of appropriability is likely to be between these two extremes. In determining the actual governance form (apart from the other TCE factors, of course), we suggest that appropriability strongly relates to another dimension: the sensitivity of the information that is (to be) shared. If appropriability and sensitivity are both relatively low or are both relatively high, the choice is predominantly determined by the other TCE factors. If appropriability however is low, while sensitivity is high, then there is -in determining the governance form in interplay with the other TCE factors- an inclination toward internalization. On the other hand, if appropriability is high, while sensitivity is low, then there is no objection to externalization.

Whether particular information is sensitive or not strongly relates to the level of competition in the industry, so will introduce this dimension by means of the factor *level of competition* subsequently. If a firm sees itself forced to expose particular competitively sensitive information, collaboration is preferred, as there are agreements in advance (prior to collaboration) about sharing costs, profits and other (dis)advantages. In that case, there is part of the spillover 'financially compensated' (and there is more of a bond so the collaborator is expected to be less likely to abuse the information in the first place). Means to appropriate ('carefully placed legal rights') might still be required (Majewski and Williamson, 2004).

Last of all, some authors take it one step further and see the 'collaboration transaction contract' as an arrangement for 'financial compensation for leaks of knowledge' and that this contract thereby restores the incentive to engage in R&D (not just R&D collaboration!) (See Sakakibara, 2002, on Spence, 1984). So, they see the contract as an essential appropriation instrument. In a fully competitive market, this is somewhat far fetched as it presumes that this 'financial compensation' covers the negative effects of externalities and direct spillover. In an oligopoly, however, collaboration will indeed eliminate a significant part of the negative consequences of externalities by converting them in paid spillover and of course will yield better technology.

Lastly, we see that the currently formulated TCE framework prevails over the traditional TCE framework. An increase in technological and market uncertainty will bring about an increase in collaboration propensity under the condition that there is a sufficient level of appropriability. Recall that the original framework did not consider these forms of uncertainty in the first place, partially due to its static nature. We have also refined the notion of behavioral uncertainty by signaling that it really is about non-appropriable spillover and externalities. We see that the 'escape' of the preferred form of governance to unilateral or market governance upon an increase in behavioral uncertainty (and even asset specificity) only holds if appropriability is at an insufficiently high level. We will later see that the 'escape' will be to unilateral governance if competition is fierce.

Complementarity

In the introduction of this section, we showed that a firm is sometimes interested in collaboration with the motivation that the other party contributes cash, knowledge, capacity and/or capabilities.

Bearing in mind that we are especially interested in the effects of technological complexity, we focus on knowledge and capabilities as incentives to collaborate in particular. Collaborating then is interesting if the partner contributes complementary knowledge and capabilities, allowing the principal firm to overcome difficulties and achieve new technological solutions. We also argued that the bigger complementarity, the more costly internalization, the more likely collaboration.
Despite the intuitively clear meaning, the concept of complementarity is not trivial to explicate. Here, we conceive complementarity as the degree to which functionally interconnected components are controlled separately. We will however see that we can relate complementarity with technological distance and link it with existing SM theory on efficiency of learning and innovative value of relationships.
We will first focus on the operational level of complementarity. We will then discuss the theory on complementarity, with exponents from Strategic Management as well as researchers working on TCE theories. We will then review the findings within our TCE model.

At an operational level, firms are said to have competences allowing them to efficiently manage particular technological components. Due to lack of competences in other areas, the efficiency or even capability to do so for other technological components is less. The extent to which a firm is in control over shaping technology to improve it is limited by its competences. From our conception of complementarity, we distinguish two dimensions: the relative contribution to control by a collaborator and the interconnectivity of components (through elements) under control that are contributed. Obviously, we can express complementarity at micro-level between two specific firms, but also at meso-level between any combination two firms in the industry.
The adequacy of the control of a firm depends on the fraction of components under control (by its competences). If the competences span most of the technological components of the system, the firm is more likely to be well capable to improve technology adequately. We however know that due to non-decomposability of technology, interference with functioning of components not within control might deteriorate the proper functioning of the whole system. The number of interconnections to components outside its competences will certainly affect the overall performance. So, we see that innovation performance increases with the span of control but decreases with the interconnectivity. Firms can now enlarge the control over technological change by collaborating. The collaborator will after all also bring in (adequate) control over particular technological components. Obviously the contribution is valued higher if this collaborator brings in control over a number of components being a large fraction of the remaining components spanning the system than if this same absolute number of components only is a mere fraction of the total number of components not yet under control. The contribution of control over complementary components might not only enlarge the number of components which can thus be improved, but will also allow to overcome part of the otherwise interfering interactions between components in their respective competences. The collaborator will then be able to signal imminent incompatibilities and preemptively suggest alternative solutions. If there are in addition technological interdependencies, collaboration entails synergistic innovation performance improvements.
If firms generally are specialized, the additional competences might be of little value, especially when facing intricate, large-scale technology. If the components under control by the different firms have only few interdependencies, there is only limited synergy from joining competences. The jointly developed technology is more or less just the combination of the individual improvements. In that case, outsourcing is a viable option. On the other hand, if firms are all-rounders and hence their competences allow control over (nearly) all components, then there is little other firms can add to what the principal firm can do.

Now that we have a clear understanding of complementarity with regard to our operational definition of technology, we take a look at theory that perceives technology predominantly as the output of knowledge and collaboration as cross-fertilizing knowledge. The general view is that learning

and innovation both increase with complementarity of the knowledge bases (Sapienza et al., 2004; Feller, 2004), with knowledge diversity (Cohen and Levinthal, 1990) and when the constituents are at some cognitive distance (Nooteboom, 2006). Although highly familiar knowledge can be assimilated and adopted efficiently (Sapienza et al., 2004), its innovation potential (Fleming, 2001) and thus the novelty value of the relation (Nooteboom, 2006) are limited. On the other hand, mutual understanding decreases with cognitive distance (Nooteboom, 2006). Highly unfamiliar knowledge is difficult to adopt and assimilate by the receiver, after all, absorptive capacity (in terms of being able to recognize and utilize the knowledge that is transferred) determines the effectiveness of the contributions of complementary knowledge (See Cohen and Levinthal, 1990; Oerlemans and Meeus, 1998). Following the theories on efficiency in learning, we expect the innovation performance of R&D collaboration and the usefulness of the spillover to depend on the technological distance in an inverted-U fashion (Sapienza et al., 2004; Nooteboom, 2006).
We can now employ the operational description of complementarity just provided and map this onto the one-dimensional scale of technological distance by realizing that the two dimensions of complementarity are not completely perpendicular! Under the condition that the scope of control of the firms is not extraordinary asymmetric, we simply argue that if the relative contribution to control is low (there hence is considerable overlap or firms are hyper-specialists), the dependency on this additional control (since the contribution is low, there are at most a few technological interconnections, regardless of the intricacy) in overall innovation performance is relatively limited. We now simply say that if the relative contribution to control is low, that technological distance is small (the firm is 'nearby'). If there are considerable contributions to control but the interdependency is low, the distance is great (the firm is 'far off'). If there are considerable contributions to control as well as considerable functional interdependencies, we say the technological distance is intermediate. Firms are -in probability- able to achieve synergistic innovation performance increases. Note that this translation is bijective as close distance implies a low contribution (moderate complementarity), far distance implies low interdependency (moderate complementarity) and intermediate distance implies considerable interdependency and considerable contribution (high complementarity)! Although our translation of complementarity into technological distance is certainly not graceful, it shows that our definition of complementarity does not exclude support for the theories on learning and novelty value of collaboration. In the remainder of this essay we will keep in mind that complementarity has two non-perpendicular, oblique dimensions which allow us to use a single value to specify both dimensions which we can easily memorize by keeping in mind our translation of complementarity into the technological distance scale.

Interpreting the findings concerning the effects of complementarity on collaboration propensity within the realm of TCE concepts, we see that if the knowledge bases and competences of firms overlap, complementarity vis-à-vis the potential collaborator is moderate to low. Since the additional control gained by collaborating is relatively low, the reduction in technological uncertainty is low as well. Now suppose that the knowledge bases and competences of firms are largely disjoint. If there is relatively little technological interdependency, outsourcing or simply acquisition on the market is a viable option as there is little technological interference on both sides and communication is required only incidentally. If there is considerable interdependency, on the other hand, firms have to intensively tune their technological components so as to overcome interferences, incompatibilities and to preclude malfunctioning upon joining components, and, so, to reduce technological uncertainty on viability. Moreover, recall that costs of internalization are relatively high due to the more than moderate technological distance. So, if there is a high level of complementarity, either internalization or collaboration is an evident strategy. Other TCE factors will come into play in further determining the exact governance form.
Under the presumption that the level of complementarity is considerable, we see that, if we want to further refine the decision whether to pursue collaboration or internalization, also the dimension

of specificity of technological complexity comes into play. From Lundvall (1990) and Nooteboom (2006) we already know that if the market is still developing, technology is not yet mature and standards have not yet emerged (hence the specificity is considerable), that, for dynamic efficiency sake, collaboration is preferred over internalization. We see this confirmed in Teece (1986) who argues that if complementary assets like marketing, production and additional techniques are freely accessible (also to competitors!), a firm can best seek collaboration with those complementary assets. If they however are highly specific, a firm can best acquire the resources and internalize these assets.
We have to acknowledge that the principal firms also has to weigh the costs of internalization versus the costs of the transaction, hereby taking into account the synergistic operational advantages and different levels of innovation efficiency, but also the leakage of knowledge. Hereby, the appropriability and level of competition of course come into play. We see that we need a profound integral look on the interplay of the factors to address this adequately and we will shed some light on it in the evaluation of our adorned TCE framework.

Let us shortly recapitulate on what we have just described. We provided an operational definition of complementarity starting with the operational definition of technology. We distinguished two dimensions of complementarity (relative contribution to control and interconnectivity of components contributed) and saw that complexity and complementarity coincidentally have the same dimension interdependency of technological components (or intricacy). We then showed that the Strategy Management theories relating (technological) distance to the efficiency of learning can be explicated in our operational framework and that we hence find support for an inverted-U relationship. The interpretation within the TCE framework of the thus obtained rationales appeared to boil down to a story of reduction of technological uncertainty. We subsequently showed that if we introduce one more dimension of complexity (specificity of knowledge) we can further refine the predictions for the governance form. We also stipulated that we need a bird-eye perspective and a sort of cost-benefit analysis of transaction costs and benefits for the various governance forms to predict the effect of complementarity in more detail.

Level of competition

We saw that the level of competition closely relates to market uncertainty and that it in fact plays a central role in determining collaboration propensity as it puts pressure on the dynamic efficiency of all parties in the sector. Here, we see the level of competition as the volatility of market shares for activities of other players in the market. Reports on the effects of competition on collaboration propensity are ambiguous, perhaps indicating our understanding is limited, perhaps insufficiently acknowledging mediating factors. We will not elaborate on intricacies, but rather touch upon two clearly distinct rationales.

Firms are supposedly not interested in collaboration in the near-market product development because the research efforts can be effectively appropriated (Ouchi & Bolton, 1988), making it worth investing especially since the market and technological uncertainty is low and little risk is involved. Moreover, collaboration in the near-market product development phase is prone to competitive conflicts (Dodgson, 1993). Under fierce competition, a collaborator is expected to be more tempted to engage in opportunistic behavior to mimic the technology of the competitor with which it is collaborating (Majewski and Williamson, 2004). Recall that we indeed already argued that the behavioral uncertainty is considerable in this phase. R&D collaboration would thus be more likely to occur in a pre-competitive, exploration phase of the industry.
More general than the danger of opportunism is the effect of spillover. In discussing the factor appropriability, we already noted that if competition becomes more fierce, sensitivity of certain information increases and the inclination toward internalization increases. We see this supported

by Von Hippel (1987) as he states that the collaboration propensity decreases if the intensity of competition increases as, indeed, spillovers can then after all be decisive (Von Hippel, 1987; Dachs et al., 2004).

If we now take an alternative perspective, we argue that competition also amplifies the effect of poor innovation performance as poor dynamic efficiency is likely to put firms at an insurmountable technological setback, makes them lose market share and income and thereby possibly forced them into demise. So, competition urges firms to overcome market and technological uncertainty by seeking complementary knowledge. We do see that several authors indeed come to this opposite conclusion: as R&D collaboration provides access to complementary knowledge, it enables a firm to further expand its capabilities and thereby strengthen its competitive position, which can be crucial in a competitive market (Sakakibara, 2002; Chen, 1997).

Let us now try to synthesize the two schools of thought. The first school of thought in fact only does an attempt to falsify that collaboration occurs in the maturation phase, and concludes from this that collaboration would then be more likely in the developing/ exploration phase.
By introduction of the factor of appropriability, we solve the apparent contradiction. In the maturation phase, we argue that complementary knowledge is still wanted, but non-appropriable spillover and the likely presence of opportunistic behavior might convince firms (collectively) to pursue the not-so-risky internalization and this way prevent spillover which might be detrimental (this is in support of the first school). Before meeting the second school halfway, we, first of all, argue that the urge for R&D performance might make firms less risk averse (more risk prone) in exposing particular sensitive information to collaborators. The trump card however is that if appropriability is high, the damage due to the moderate non-appropriable spillover is outweighed by the gains in complementary knowledge. If a few firms thus enjoy improved dynamic efficiency, it becomes a competitive advantage (especially since collaboration strongly amplifies dynamic inefficiencies), thereby forcing other firms to follow in similar strategic behavior.
As far as the development phase is concerned, we still argue that the abundance in opportunities and too great a technological distance makes firms reluctant to collaborate.

Let us interpret this factor level of competition within the traditional TCE framework. We already know that if appropriability is sufficiently strong, appropriation instruments overcome opportunistic behavior and presses the transaction costs (by supplementing the contract and reducing the need for control). If the level of competition increases, the dynamic efficiency becomes more crucial in survival. If the level of appropriability is sufficiently high, firms look for complementary knowledge through externalized governance forms. In this case, our theory concurs with the second school of thought. If appropriability is insufficient, transaction costs of external solutions become high (in guarding oneself against opportunism, checking whether the collaborator complies with contractual arrangements and possibly taking legal counteractions). Firms are then likely to completely internalize R&D. In this case, our theory concurs with the first school of thought. We see that the level of appropriability intermediates the relationship of the level of competition with the collaboration propensity.

Evaluation

We now have implemented the amendments to the TCE theory and framed several specific Strategic Management theories to establish the adorned TCE framework we will use to predict the inclination to select particular R&D project governance forms. It is important to realize that the model does predict collaboration propensity within an industrial sector, so at meso-economic level, rather than the precise governance form chosen for a particular R&D project. We will now zoom out and evaluate the relationships of the various factors with each other and the relationship with collaboration propensity.

The general idea behind this adorned TCE model is -in short- that if technological complexity is high, pursuing collaboration to seek technologically complementary knowledge reduces the (inherent) technological uncertainty and thus gives a competitive advantage (in terms of better performance). In picking a particular governance form, firms need to take into consideration the costs of internalization versus the costs of non-appropriable spillover, hereby taking into account the innovation performance in both situations including the synergistic dynamic efficiency gains when working together. This notion confirms Teece (1986) in that if spillover is appropriable and in the meanwhile complementary assets are freely accessible (i.e. are generic), a firm is likely to collaborate; internalization would be costly and it does not give a competitive advantage, while this firm does not suffer from spillover and can hence collaborate which is cheaper anyhow. On the other hand, if complementary assets are specific or the firm suffers ill-appropriability, a firm can best internalize; internalization excludes access to the complementary assets by competitors and gives a competitive advantage while collaboration would make a firm suffer serious consequences of spillover.
We see that the level of competition plays a prominent role, and, as we already signaled as well, in the face of competition, appropriability of spillover strongly determines to which side the scale is going to tip. Competition, on the one hand, urges firms to be dynamically efficient and hence urges seeking complementary knowledge, but, on the other hand, makes the consequences of outgoing non-appropriable spillover extraordinarily detrimental. So, if we extend Teece's notion of complementary assets to complementary competences and knowledge, Teece's observation can be reformulated into a more generic conjecture. Collaboration typically only occurs if the returns from R&D are sufficiently appropriable and the level of non-appropriable spillover is modest and thereby clearly outweighed by the contributions (in terms of complementary assets and knowledge or decrease in costs or development time) of the collaborator. If competition is fierce, the negative effects of spillover and externalities become more detrimental, the advantages of involving a collaborator with complementary knowledge become less effective due to the limited opportunities and this while the innovation performance increase is required more than ever to set back the competition.
If there is an insufficient level of appropriability and too much non-appropriable spillover, then the firms are forced to use the collaborative R&D contract as appropriation instrument. In that case, we see that the transaction costs increase (costs to cover holes in the contract, the costs of managing the R&D project information flows, the costs of checking whether and forcing that the partner is complying with the contractual agreements). This, in turn, makes the scale tip to internalization of R&D.

We have thus established a concise, integrated conceptual model that allows us to predict the collaboration propensity by assessing the technological complexity, complementarity, appropriability and the level of competition.

2.3.2 Sector differences

In this subsection, we will provide the empirical findings on the collaboration propensity in different sectors as found in empirical literature. Although it is possible to describe each TCE factor in representative, stereotype high-, medium- and low-tech sectors, we focus on the effects of complexity on collaboration propensity and the mediating role of the other TCE factors. We will elaborate on this method, describe the reasons to follow this method and the implications of doing so. We will then show that we can (loosely) associate complexity with the technological intensity of the sector we discuss and subsequently derive claims on the mediating effects of TCE factors on the relationship between complexity and collaboration propensity.

Empirical findings

Recall that we started out this research by observing that there is much R&D collaboration, but that there is some controversy on whether or not this is primarily confined to the high-tech sectors. In Hagedoorn (2002, 1993), the MERIT-CATI database is used to observe that R&D collaboration propensity increasingly occurs in high-tech sectors (which confirms findings of Dodgson, 1994), e.g. the pharmaceutical, IT and aerospace & defense sectors and decreasingly occurs in the medium-tech sectors, e.g. the instrumentation & medical equipment, automotive, consumer-electronics and chemical sectors. R&D collaboration hardly occurs in low-tech sectors, e.g. food & beverages, metals, oil & gas.

Dachs et al. (2004) used the CIS3 database on innovation in Austria and Finland. In contradiction to Hagedoorn's findings, they discovered that especially firms in medium-low-tech sectors seem to collaborate. They themselves argue that the collaboration propensity is determined considerably by country specific policy arrangements and other factors in the National Innovation System.

As far as the discrepancy in findings goes, analysis with our adorned TCE framework might reveal that there are low levels of standardization in those medium-low-tech sectors due to which the natural intricacy of those technologies with many components from diverse disciplines is in full effect. Firms need to be overcome this technological intricacy to lever the R&D performance. ~~Analysis with our TCE framework might also reveal that there are different levels of knowledge~~ dissemination in the various sectors. The National Innovation System might contain universities that are strongly geared toward generic application of fundamental research in commercial business, making collaboration of private firms less of an necessity. Although we see that we have a limited understanding of what causes R&D collaboration in the various sectors, we feel that the TCE framework is likely to provide additional insights in explaining the discrepancies in findings.

Regretfully, most of the papers we have examined only poorly specify the properties of the sectors. Not only that, but they also rather investigate the *motives* for firms to engage in collaboration. To a certain extent, motives are *subjective* and need not reflect generic properties of the sector. Finding *objective* assessments of the level of complexity, the overall complementarity (of capabilities and knowledge bases) of firms, the level of appropriability and the fierceness of competition for the various sectors will prove a daunting task. As we will see in the next paragraph, we moreover need an isolated description of the role of each of those factors.

Restrictions to our assessment and the method followed

The current research design is geared toward studying the effect of technological complexity on collaboration propensity. Starting from the TCE theory on the governance form to select in R&D, we resolved outstanding critique, disaggregated the uncertainty dimensions up to the level of SM factors and thereby succeeded in deriving a specific conceptual framework. We have seen that, apart from technological complexity, also the factors appropriability, complementarity and level of competition play a prominent role.

Although we based our main hypothesis on the observation that collaboration occurs more in high-tech sectors, it is important to realize that we are not analyzing the collaboration propensity in high-tech versus in non-high-tech sectors, but that we are isolating the role of complexity in that. As sector 1 might have a different configuration of those four TCE factors than sector 2, we would have to control for all the (operationalizations of the) factors at once. In the encompassing research design, we would have to compare the output for the sector 1 configuration with the output for the sector 2 configuration. Hereby, sector 1 and 2 might have different levels of complexity, complementarity, appropriability and level of competition. Note that it would become difficult to

discern effects of complexity and the (intermediating) effects of the other TCE factors[8].
In order to get a clear image of the effect of complexity, we have agreed to limit our survey of the parameter landscape and to come to a more straightforward research design. Hereby, we *vary* complexity and control one of the other TCE factors (while maintaining the other factors at a relatively neutral level) and inspect the effect on collaboration propensity.
It should however be noted that there is a clear objection to this practice. Suppose we compare a stylization of a high-tech and a non-high-tech sector. Even if we would distinguish only two levels per factor (including complexity) and inspect only two factors each time, we would have at least 2 out of 4 combinations that do not square with the configurations of the two sectors we compare! By controlling for the TCE factors, we can hence not only investigate whether the factors have the presupposed effect on collaboration propensity when meeting the right configuration, we can -focusing on complexity as main factor- also investigate the effect of variation of the other TCE factor on collaboration propensity. So, per intermediating TCE factor, we will try to: (a) pinpoint the level of the intermediating TCE factor and its effect in case the sector is high-tech and in case the sector is non-high-tech such that we can later verify occurrence of the effect, and (b) describe the effects of variation in the intermediating TCE factor which would allow us to determine the validity of our operational model and test the implications of our conceptual understanding.

In our description of the (intermediating) effect of one of the TCE factors on the relationship between technological complexity and collaboration propensity, we will use, on the side, that high-tech sectors generally have a science-based regime, low-tech sectors generally have a continuous-process regime, while the medium-tech sectors generally have a product-engineering, complex-systems or fundamental-process regime. The properties of those regimes have been described in detail in Marsili and Verspagen (2002).

Effect of complexity in conjunction with other TCE factors

We will now describe the effect of each of the other TCE factors on the relationship between complexity and collaboration propensity, and we will assess the effects of the TCE factor in both the high- and the non-high-tech sector. We will first look at technological complexity in the high- and non-high-tech sectors in isolation. From that, we will see that we can -for our purposes- loosely associate technological intensity with (two generic dimensions of) technological complexity. We can henceforth limit ourselves to specifying the level of technological complexity to isolate the type of sector we are discussing. Subsequently, we will describe the effects of each of the remaining factors (appropriability, complementarity and level of competition) in conjunction with technological complexity on the collaboration propensity.

From Hagedoorn (1993) we know that low- and medium-tech sectors generally are more mature than are high-tech sectors. Although medium-tech sectors with a complex-system regime have intricate technologies requiring products from many other disciplines, the high level of standardization and maturation of the technology allow focusing R&D on particular components. In high-tech sectors, much knowledge is not yet publicly available and has yet to be disclosed by fundamental, academic research, standards are virtually absent and applications are highly specific (also see Marsili and

8. Discarding this approach is certainly not because of technical or practical reasons as we can both assess the real values of these TCE factors and we will be able to set the TCE factor operationalizations in the Neo-Schumpeterian model established in chapter 5. In an early draft, we, as a matter of fact, already had assessed the four factors (and their dimensions) in high-, mid- and low-tech sectors. We did not gather the required information sector-by-sector, but inferred on the sectoral pattern of technological change by looking at the properties of the underlying technological regime (see Breschi et al., 2000). We mapped the classification of sectors into high-, mid- and low-tech as established by Eurostat (2006, p.201) onto the Marsili and Verspagen (2002) classification of technological regimes (which is an extension of the taxonomy of Pavitt (1984)). We then relied on the more thorough treatise of the properties of the various regimes to infer on the factors that determine R&D collaboration propensity.

Verspagen (2002) on this last account), so firms in these sectors face highly specific R&D and a considerable task in discovering low-level, fundamental knowledge.
From Marsili & Verspagen we also know that the diversity of disciplines (or differentiation of the knowledge base, as they call it) is relatively low in many high-tech and medium-high-tech sectors (science-based and fundamental-process regimes), while it is relatively high in the other sectors (the other three regimes). We conclude that particularly the high-tech sector has a low diversity that is presumably caused by a strong focus on fundamental, academic research and less on the actual engineering.
If we now take the stance of an R&D engineer, the medium-tech (and perhaps even the low-tech) sectors might have more disciplines and more technological components involved, the technology in the sector is more mature. Technological design and interfaces are well-defined, components well-available and the technological knowledge required for innovation generally available (less specific). In the high-tech sectors, the technological knowledge is highly specific and the technical elements to be combined in innovation are non-standardized making recombination and innovation suffer greatly from the non-decomposability. As such, we see that from an R&D engineering point-of-view, innovation in high-tech sectors is certainly more complex. To put it more firmly: if a sector is mature and technological knowledge is generic, no matter the underlying intricacy, (non-synergetic) innovation is non-complex. Let us henceforth associate the classification of high- and non-high-tech sectors with technological complexity (and then particularly the dimensions of specificity/maturation and non-decomposability of the technology principal to the sector).

Let us now look at the effect of complementarity in conjunction with technological complexity (on the sector difference) in collaboration propensity. Complementarity can be seen as a motive for collaboration as well as an underlying property of the distribution of the technological knowledge over the various parties in the sector and the diversity of the disciplines involved in the technology. Hagedoorn (1993, p.379) finds that complementarity is less of an incentive in low-tech (food & beverages) and medium-tech (consumer electronics, chemicals) sectors, while it is a strong incentive in high-tech (industrial automation, software, new material technology, biotechnology, aviation & defense, instruments). Hagedoorn (1993, p.378) argues that seeking complementarity in those sectors is to be seen as attempts "to cope with complexity and interrelatedness of different fields of technology and their efforts to gain time and reduce uncertainty in joint undertakings during a period of growing technology intricacy". He continues by arguing that sectors like chemicals, consumer electronics and food & beverages are somewhat more mature and reasons to collaborate primarily relate to influencing the market structure.
Recall that complementarity has two dimensions: the relative contribution to control and the interconnectivity of components that are contributed by the collaborator. Although many non-high-tech sectors might well have a regime involving more disciplines and more components, the maturation and standardization has reduced the net complementarity. During early phases of industrial development, there is segmentation and specialization making contributions to control increase in value (under the condition that the firms in question are not hyper-specialists) but then standardization of interfaces of components (especially those belonging to different disciplines) reduces the interdependency. We hence see that with the development of the sector, the 'relevant' intricacy diminishes as only part of the underlying interdependencies are at stake during R&D while the others are 'fixed' by standards, conventions and agreements. In these phases, only firms trying to overcome interface limitations to achieve synergistic innovation will collaborate, but otherwise outsource or internalize R&D. In later phases, firms integrate vertically and horizontally, hereby expanding the possibilities for internal synergistic innovation, but limiting the contribution of potential collaborators. In both cases, the technological uncertainty concerning complementary components is relatively low and, as such, collaboration for complementary knowledge is unlikely.
We see that if the sector is high-tech (non-high-tech), technological complexity (and in particu-

lar the dimensions non-decomposability and specificity/ maturation) is high (moderate to low), then firms seek (do not seek) complementary knowledge. We also see that two of the four 'free combinations' are unlikely: the combination of high complementarity and low complexity or low complementarity and high complexity do not occur in reality.
We expect that complementarity amplifies the positive effect of complexity on collaboration propensity. After all, the innovation performance augmentation realized by collaborating rather than working solo also increases with an increase in complementarity.

Let us now look at the effect of appropriability in conjunction with technological complexity on the sector difference in collaboration propensity. We will follow Kim and Vonortas (2003) and Cohen, Nelson & Walsh (2000, 2002) in arguing that appropriability often is higher for technologies of low complexity (e.g. ferrous and non-ferrous metals, chemicals, petrochemicals, drugs, food, tobacco) than is for technologies of high complexity (e.g. machinery, computers, electrical equipment, scientific instruments). They argue that simple technologies comprise of only few components that need patenting to block imitation, while complex technologies comprise of many components, which makes patent circumventing easier.
These authors might be right if a significant part of the specifications of the technology is disclosed or publicly available, but complexity of technology *inherently* relates positively to appropriability. After all, simple (complex) technology is easy (difficult) to reverse engineer. Complex technology hence has a high level of so-called inherent appropriability. If we look at the dimensions of complexity, we see that possible causes are the specificity of knowledge involved, the level of standardization and maturation of the technology or the non-decomposability so apparent in intricate technology. So, means of appropriation are effective in case of simple technology but also still needed as it is relatively easy to reverse engineering and imitate that simple technology. The immediate necessity to employ appropriation instruments is less apparent if technology is complex. When looked at the other way around: if appropriability is low due to insufficient legal means, then secrecy, lead time and even design complexity are crucial competitive advantages (Dachs et al., 2004).
We see that these claims generally seem to hold for less-adherent technological knowledge, but tacit, non-codified innovation engineering knowledge that has not yet materialized in production technology is difficult to protect. Adherent spillover provides competitive advantages to the receiver, so we presume that firms care less about non-adherent spillover/ externalities than about adherent spillover. Especially if the competition is fierce, firms are expected to become more hesitant to collaborate if they expect (asymmetric) outgoing adherent spillover. Note that in non-high-tech sectors, the technological distance is low and the receiver can easily absorb the adherent spillover. Since competition is relatively fierce in those sectors, the spillover is expected to be more detrimental to the competitive position of the original firms. In high-tech sectors, complementarity is relatively higher, the technological distance between the collaborating firms is higher and competition is lower, so we expect adherent spillover to be less of a problem.
All in all, we expect firms to be reserved in sharing innovation engineering knowledge, but are less worried with sharing 'recipes' of technologies.
The level of inherent appropriability and the availability of instruments to enforce appropriation of course affect the R&D (collaboration) propensity, but we can conclude little from observing traces of appropriation (e.g. patents). After all, employing instruments for appropriation can depend on the technology-regime itself (See Malerba and Orsenigo, 1996), the level of competition and on country-specific legal frameworks, et cetera. Since we expect that the lion-share of spillover will concern non- or mildly-adherent spillover, we expect that, in general, low complexity is coupled with high appropriability and high complexity with low appropriability. The other combinations are argued to be less likely. Apart from the probability of certain combinations, if we look at the effect for a *fixed* level of complexity, the effect of appropriability on collaboration propensity is expected to be weak (strong) if complexity is high (low).

We expect that appropriability amplifies the positive effect of complexity on collaboration propensity. After all, the detrimental effects of spillover and the transaction costs (covering contractual holes, verifying compliance with that contract et cetera) diminish.

Let us now look at the level of competition in conjunction with technological complexity and the way that these factors affect the collaboration propensity in the high- and non-high-tech sectors. The level of competition of the sector is assessed by evaluating the extent to which there are entry barriers and the market concentration. In grasping the effect of the fierceness of competition (and its dimensions) on the collaboration propensity in the various sectors, we should ideally create a profound understanding of the way in which technological opportunities, technological & market uncertainty and the population composition co-evolve. This is such a broad research topic, that it is out of the scope of this essay. We however can conclude from Marsili and Verspagen (2002, 2001) that high-tech sectors (with science-based regimes) have high technological opportunities and high market concentration, while non-high-tech sectors have less technological opportunities and lower market concentration. The rationale is that upon maturation of the technology, standards get defined, opportunities decrease and dominant designs emerge. This causes entry barriers to drop, imitators to enter and subsequently the concentration to decrease. We hence expect that high-tech sectors suffer high technological complexity but low levels of competition. With maturation, this complexity (through *relevant* intricacy) decreases and hereby the competition increases.
As argued in 2.3.1, the level of non-appropriable spillover in fact mediates whether complementary knowledge is sought after if competition increases. In high-tech sectors, the low level of competition and high dependency on complementary knowledge make firms eager to collaborate. The level of non-appropriable spillover then in fact determines whether firms will actually do so or not. If the level of competition now rises in such a high-tech sector, dynamic efficiency becomes more crucial and, hence, the spillover is likely to become more detrimental. So, with an increase in the fierceness of competition, the extent to which there is non-appropriable spillover gets more weight in the decision whether or not to collaborate. The effect of competition on the weight of the level of non-appropriable spillover in deciding whether or not to collaborate is weaker in non-high-tech sectors as complementary technological knowledge is less sought after.
We expect that competition amplifies the effect of complexity of collaboration propensity as the consequences of the (net) advantages and disadvantages on dynamic efficiency become stronger.

In the conclusions in chapter 7, we will confront our assertions on the effects of the factors in high-tech and non-high-tech sectors and our expectations of the intermediating effects of the factors on the relationship between complexity and collaboration propensity with the actual simulation findings. A quick reference to our assertions and expectations can be found in table 7.1.

Chapter 3

Survey of existing models of R&D and R&D collaboration

In section 2.2, we provided an introduction to the class of Neo-Schumpeterian models in which, typically, a set of micro-level agents that conduct boundedly rational R&D in (implicit) interaction with the shared economic environment is subjected to evolutionary forces so as to study emerging (meso-level or typical micro-level) behavior. As argued, such a model is particularly suitable to address the main research question we posed ourselves. In order to establish such a model, we clearly need to operationalize (collaborative) R&D and thereby be able to vary 'technological complexity' and allow for preference of conducting R&D solo or collaboratively to emerge endogenously. This chapter concerns a survey of models that either already do so, provide clues on how to do so or one way or the other provide us with components we can use in our own model. First of all, we of course are interested in (Neo-Schumpeterian) models already around that also facilitate emergence of R&D collaboration. We can distinguish three functional components of such a Neo-Schumpeterian model. The framework that brings about emergence of behavior (*what drives emergence*), the factors that ~~determine which agents survives and more specifically what strategy features~~ (~~*what assures agent*~~ *survival*) in what economic environment (*under which conditions*).
Firstly, the 'set of conditions' spanning the economic environment of course is closely related to the operational definition of the circumstantial factors at work in the conceptual model. In current Neo-Schumpeterian model, this economic environment usually is very basic to be able to disentangle cause-and-effect chains from the already complex, non-linearly produced simulation results. Secondly, the 'driving of emergence' is of course taken care of by the Neo-Schumpeterian framework which is firmly rooted in economic rationales (other options are e.g. genetic programming or birth and death rules like in Conway's life which typically (allow) follow(ing) other than strictly economic rules). This Neo-Schumpeterian framework is program-technically easy to establish and it is tempting to see the framework as a tool. To use the Neo-Schumpeterian framework, however, imposes constraints upon the models of the economic context, the agent and operational R&D model framed within the framework. These constraints obviously are the assumptions that Neo-Schumpeterian models inherited from the underlying Evolutionary Economic theory. Thirdly, as far as the 'what assures agent survival' component goes, we can distinguish (see the subsection on agent heuristics in section 2.2) both a representation of the operational R&D and heuristics to cope with the economic environment. The model of *how* R&D is conducted *operationally* is usually introduced by means of technology landscape search model. We are also interested in heuristics that determine *when*, *in what form* (solo or collaborative) and -if in collaboration- *with whom* to conduct R&D. The 'collaboration strategy' regularities are actually emerging, and therefore the hypotheses usually predict when, which form and with whom (or some aggregate product thereof, like e.g. the topological properties of a network emerging).
The designer of the Neo-Schumpeterian model typically experimentally controls (a) factor(s) in the economic environment or the technology landscape being searched to study the emerging behavior (or indeed an aggregated product thereof). The factors controlled for of course are operationalizations of the independent variable(s) in the causal relationship under study, while measures of the emerging behavior generally are aggregated into an operationalization of the dependent variable(s) in that causal relationship.

We will use this typification in section 3.1 to describe fully-fledged models of R&D collaboration found in literature. As we will see, the core economic environment models in such fully fledged R&D collaboration models depart considerably from our conceptual (adorned TCE) model. In addition, none of the operationalizations of the core R&D model, i.e. the technology landscape search models, we discerned in these models allows tuning technological complexity or facilitates operationalization of factors in our conceptual model (e.g. appropriability). In fact, they do even feature a defective evolutionary framework! So, from looking at these models we learn the tricks-of-the-trade, but we can not entirely rely on models already developed.

Perhaps we should shift our attention from fully-fledged models to more fundamental models of R&D collaboration to see whether there are candidates eligible to be used by us. We already established that the selection device in the core evolutionary framework actually not so much depends on the way R&D is modeled (operationally) as long as the output of R&D is translated into an ordinal performance measure (such that we can deselect poorly performing agents and have superiorly performing agents propagate their traits/ strategies). In that case, a properly functioning evolutionary framework (in narrow sense) would automatically take care of emergence. So, one of our primary concerns is the specification of collaborative R&D. As such, we will also conduct a survey of low-level, more fundamental models of operational R&D collaboration that are eligible to be plugged into our simulation model. As said, such a model should facilitate operational definitions of factors in our conceptual model (e.g. appropriability (for which we require an operationalization of spillover), complementarity (requiring agents to be confined to part of the landscape), the level of competition, et cetera) and it should be possible to order the outcome of R&D. We will present the results of a small survey in section 3.1.2.

As we will see, the technology landscape search in these fundamental models of R&D collaboration is modeled in numerous different ways, where the actual definition often also closely relates to the conceptual, causal relationships under study. Often not only the conception of technology (e.g. (vector of) knowledge, set of capabilities, set of elements, process efficiency, capital-labor ratio) or conception of collaboration (e.g. mutual increase of capabilities, cross-fertilizing of knowledge, displacement in ratio, exchange of component recipes) are just different. There often is some variable feature of technology (e.g. ease of integration, modularity, distribution of opportunities) that is (supposedly) affecting R&D behavior.
Although we -in retrospect- already find the model of operational R&D collaboration that we will use among the fundamental model of R&D, we will in subsection 3.2 also present the results of a small survey of basic technology landscape models (that not necessarily already feature R&D *collaboration*) found in literature. As such, we will not miss out on good options and also show that the NK landscape -which we decided to use at the outset of this research- is a promising, versatile model that indeed enables us to operationalize factors in the conceptual model more than any other technology landscape.

Let us now, first of all, present the models of R&D collaboration, as said, the fully fledged models and the fundamental models, and, second of all, the technology landscape search models.

3.1 Models of R&D collaboration

R&D collaboration is defined as the process in which two or more agents recombine and/or exchange technological knowledge or technology instances. This definition is broad, on purpose, as it allows classifying numerous concepts as collaboration, e.g. 'one-shot' exchange of technology instances, iterations of insertions of elements into a shared technology instance, persistent co-development of new technology instances using their respective technology repositories even up to cross-fertilization of technology expertise (and thereby alter output or performance).

In our treatise of models of R&D collaboration, we will completely focus on Neo-Schumpeterian simulation models. Here, we will review several of such models found in literature.
As each of these models appears to be geared toward studying particular phenomena, we need to specify the subject of the study. Often this also has implications for the way technology and innovation are conceived and codified, which we hence also have to specify. As we saw in the examples just

given, collaboration can be modeled in various ways, often also related to the technology conception and the goal of the paper, so we will pay special attention to the conception and implementation of R&D collaboration. Although it is well possible agents compete with the technologies they collaboratively produced, R&D collaboration is at the outset *not* competitive[1]. It is furthermore of interest how agents come to their decision to collaborate (rather than e.g. do nothing or work solo) and how they determine with which agent to collaborate.

Apart from these issues, we will also evaluate the typical Neo-Schumpeterian model dimensions. Particularly important of course is how the evolutionary framework has been integrated and extent to which this enables the researcher to study industrial dynamics.
To go short, we will be looking at:

- Research subject of the study.
- Codification and conception of technology and of technology improvement.
- The conception and implementation of collaboration.
- R&D strategies and action decision heuristics of agents.
- The mechanisms of selection, the sources of novelty and variety.
- Schumpeterian innovation approach to industrial dynamics.

The focus is on the actual model rather than on the specific outcome of simulations, so actual findings and conclusions of the studies will *not* be discussed. A more detailed treatise of the codified forms that technology takes and how innovation is perceived is discussed in the subsequent section on technology landscape search.

We have divided the models in literature into two classes: fundamental models of R&D collaboration and Neo-Schumpeterian models of R&D collaboration. The models in the first class typically lack evolution and certainly the possibility to model industrial dynamics. The models in the second class often are designed to study the events in a fully-fledged industrial sector, hereby incorporating many factors to add to realism. Some go as far as trying to reenact real strands of history. We will now first discuss a couple of such fully-fledged models and then focus on the more fundamental models of R&D collaboration.

3.1.1 Neo-Schumpeterian models of R&D collaboration

We will discuss two models:

- A conceptually rich model by Nigel Gilbert, Andreas Pyka and Petra Ahrweiler used in the extensive SEIN project to 'reenact' actual instances of industrial development.
- A model by Lorenzo Zirulia of network dynamics.

The Gilbert et al. (2001) model is developed to study properties of innovation networks. Agents generate artifacts and can subsequently improve those artifacts alone or collaboratively. An Innovation Oracle attributes those artifacts a fitness value based on criteria not known to the agents. Each agent i has a so-called KENE (see Gilbert, 1997) which is a set of triples of technological capabilities C_i^j in different technological fields j, its specific ability A_i^{jm} in this field and its level of expertise E_i^{jm} concerning this ability. Each period, a so-called 'innovation hypothesis' is formulated by drawing a number of triples from the KENE. The expertise level of triples that are (not) selected increases (decreases), which models learning-by-doing, learning-by-using and forgetting. At the end of each period, the innovation hypothesis is submitted to the Innovation Oracle. This oracle attributes a financial reward according to the fitness of the innovation hypothesis on a multi-dimensional, multi-peaked landscape. That is, if the fitness is high enough. After having disbursed

1. This allows us to exclude *strategic interaction* models using Game Theory (See e.g. Fagiolo et al., 2005; Tesfatsion, 1998; Alkemade, 2004) and bargaining models with evolutionary trained offers (See e.g. Van Bragt et al., 2002). These models can however of course be used for negotiation prior to engaging in the actual R&D collaboration, or in the marketing model (e.g. to determine the output quantity or price).

the payoff, the point on the landscape is deformed such that rewards are not paid multiple times for the same innovation. Nearby locations however are made more attractive to introduce the concept of imitation into the model. If the reward is sufficiently high, a new spin-off agent is introduced which is a randomly mutated copy of the KENE of the successful innovator.
Research strategies are modeled as operations on the KENE. This way, agents move about the reward landscape, hopefully toward regions with (sufficiently) high rewards. An agent can follow any of three strategies. An agent can pursue R&D alone: the *do-it-alone* strategy. An agent can focus on collaborating, but refraining from conducting R&D, i.e. trying to copy KENEs as a freerider: the *imitative* strategy. Finally, an agent can focus on both collaborating and conducting R&D: the *collective* strategy.
Incremental R&D is modeled as replacing an ability A_i^{jm} of capability C_i^j with a new one, say $A_i^{j\hat{m}}$, and hereby starting with $E_i^{j\hat{m}}$ equal to one. An agent follows a simple hill-climbing rule: if changing the ability was beneficial, continue, else select the ability of another capability at random. Radical R&D is modeled as drawing a new triple for the innovation hypothesis. The agent will resort to radical R&D if incremental R&D fails to yield the desired payoff repetitively.
Gilbert et al. (2001) furthermore distinguish two types of collaboration: bilateral collaboration, a 'one-shot exchange' of knowledge, and a research network, a long lasting relationship. Each period, agents will advertise their capabilities present in their last innovation hypothesis. The attractiveness of potential partners relates to the number of capabilities they have in common. This captures the fact that it is easier to integrate knowledge if the agents have more capabilities in common. Agents also prefer collaborating with an agent they have already collaborated before. If both agents agree, they start a partnership and cross-fertilize their KENEs. Both agents involved submit an identical innovation hypothesis and share the reward in proportion to their capital stock.
If a partnership reoccurs, one of the constituents can invite the other agent to become part of a network. The other agent can only accept and join this network if this agent is not already part of another network. An agent can however have partnerships even if it is part of a network. One of the network members can invite another agent to join only if this particular agent has been partner of each of the network members. Each of the members can conduct incremental and radical innovation and engage in partnerships, but the agents share the results of incremental research with all other members. Due to the sharing of knowledge, they again submit the identical innovation hypothesis and share the payoff. If a long series of failures occurs, the network dissolves and the agents continue operating alone.
An agent has to deal with various expenses. Costs are involved in both types of R&D. There are coordination costs involved in engaging in partnership and networking although these costs are less than the expenses for solo R&D. The agent furthermore has fixed periodic costs. The capital stock is incremented with the rewards disbursed by the oracle. As soon as the capital stock is depleted, the agent exits the system.
Two case studies conducted within the Self-Organizing Innovation Networks (SEIN) project have been 'reenacted' using the KENE simulation model. Apart from succeeding fairly well, the authors themselves conclude there is yet much to be done, especially in conducting sensitivity analysis and using the model to investigate what makes the agents to prefer acting solo over collaborating and what determines the connectivity of the network.

Zirulia (2004) investigates the joint dynamics of an R&D network and the market structure. There is a population of agents producing a homogeneous good. Each period consists of a network phase during which each of agents can reset alliances (and the graph representing the R&D network of connected agents hence gets updated) and a competition phase where agents actually compete on the product market.
Each agent has a two dimensional technological capability spanned by productivity efficiency (determining the unit cost of production) and technological specialization (used to value collaborations).

	Gilbert et al. (2001)	Zirulia (2004)
Subject	Network properties	Network properties
Technology	Set of KENEs (techn. capabilities)	Technology capability vector
Innovation	Incremental: Replacing ability Radical: Drawing new KENE triple	(Only by collaborating)
Collaborative R&D	Crossbreeding KENE	Shift in technological position Reduction of unit cost of production
Collaboration options	* Free-riding / Contribute * Alone / Bilateral / Network	Break or connect relationship based on estimate of profit
Collaboration criterion	Attractiveness of partner: 1. Abilities in common 2. Past experience	Attractiveness of partner: 1. Technological proximity 2. Efficiency of collaborator
Evolution: Selection	Exit by bankruptcy (Costs vs Payoff by Oracle)	Exit if quantity to prod. drops to 0 (Cournot game dep. on unit cost)
Evolution: Novelty	No entry. No endogenous mutation	No entry. No endogenous mutation
Industrial dynamics features	Development of frontier	Development of frontier
Main indep. variables	Any allowing for calibration, e.g. * Initial distribution of actors (large, diversified versus dedicated firms) * Technical heterogeneity * Value of assets	* Opportunities * Availability of potential partners

Table 3.1: Neo-Schumpeterian Models of R&D collaboration

Market demand is determined endogenously by the quantity produced, while the individual quantities are determined by a run of a Cournot game (hereby taking the unit cost of production into account). If the quantity produced by an agent drops to zero, the agent exits. Entry is omitted from the model.
In the network phase, collaborating agents recombine their knowledge to reduce production costs. The knowledge gain is the product of the efficiency of the collaborator and the value of a function in technological distance between the firms. The latter function is a concave parabolic curve to meet the idea that collaborators need to be "not too distant, not too near" (See Nooteboom, 1999). The technological distance is measured as the difference in technological specialization. The change in production efficiency is relative to the changes of other agents and has an element of decreasing returns. Furthermore, if the agent collaborates, the specialization is also updated using a weighted average of technological positions of collaborators.
Each period, precisely two randomly drawn agents are allowed to change their collaboration state (i.e. either start or end collaboration). An agent breaks an existing alliance if profits *without* the alliance and the saving on the R&D cost exceed the profits *with* the alliance. As Zirulia argues this myopic rule-of-thumb meets the condition that agents suffer bounded rationality when it comes to estimating future returns.
Simulations showed that the R&D network is a strong selection device - agents that fail to join the network or that occupy weak positions on the technological landscape are forced into demise. Albeit agents are ex ante similar, the selection mechanism creates ex post asymmetries. Furthermore, the network becomes increasingly connected over time.

Although we will evaluate the results in more detail in 3.1.3, the features of interest mentioned in the introduction of this section are summed in table 3.1.

3.1.2 Fundamental models of R&D collaboration

We will discuss three models:

- An elegant model of bilateral knowledge production involving only several variables by

Robin Cowan, Nicolas Jonard and Jean-Benoît Zimmermann.

- A fresh model involving a non-trivial structure of knowledge by Richard Taylor and Piergiuseppe Morone, which is a "brilliant example of an agent-based model" according to the EMAEE 2005 discussant John Foster.
- The intriguing fundamental Kauffman NK landscape model as presented in Kauffman (1993) and various papers.

Cowan et al. (2004) investigate the type of networks emerging from bilateral R&D collaboration. The output of R&D is the knowledge accumulated and the patterns of knowledge accumulation over time. In this model, there is a population of agents of fixed size. Each of the agents is associated with a vector of knowledge elements. Innovation is conceived as recombining knowledge. Each period, each of the agents can decide to form an alliance or work solo. Collaboration of two agents is modeled as 'cross-fertilization' of the two knowledge vectors element-wise and hence creating a pooled knowledge vector. The authors conceive this pooling of knowledge as execution of different tasks, one task for every knowledge element. Each task is ideally executed by the most experienced agent. The more separable the tasks (in their model, the higher θ), the closer the element expertise in the pooled knowledge vector is to that of the most experienced agent. If the tasks are hard to separate, the final element expertise is closer to that of the least experienced agent. Because of this mechanism, an agent looks for a partner similar to itself if tasks are hard to separate, and a partner complementing its knowledge if tasks are highly separable (See Cowan et al., 2004, p6).
In seeking a partner, the agent uses a refined instrument based on the expected amount of knowledge being produced. This in fact is the product of the probability that the innovation succeeds and the amount of knowledge that will be produced according to a production function $\phi : \mathbb{R}_+^{\mathbf{m}} \rightarrow \mathbb{R}_+$ taking the pooled knowledge vector as input. The probability of success is based on the 'credit' of a pair, which is just a quantification for the (discounted) success of collaboration in the past, both between the two potential partners (with weight α) as well as the partners they both had in the past (with weight $1-\alpha$). If the innovation project is successful, an element of the pooled knowledge vector gets absorbed with a probability proportional to the height of the expertise.
The authors systematically investigate the (α, θ) parameter space and study the network metrics (degree connectedness, average path length, centrality and (excess) cliquishness) of the emerging network as well as the knowledge distribution in terms of a knowledge coefficient and specialization using a Herfindahl index.

Taylor and Morone (2005) study partnering in acquisition of knowledge. As the paper has been written for a conference and regretfully does not yet contain rigorous analysis of their model, the model contains a fresh concept of technology and innovation and particularly their irregular, structured technology landscape is promising.
The model has a number of agents distributed over a large grid, where each agent is able to 'partner' with another agent within a particular predefined vicinity. At system level, there is a firms' skills universe (FSU) which is defined as a directed tree with a single root node to which arcs are added in such a manner that some 'child' nodes have multiple 'parents'. The pictures perhaps look most like a 'river delta' with many branches. Each node represents a particular skill, and, as such, the skill universe is a natural representation of the fact that an agent has to possess particular skills to master new, more advanced skills. An innovation is represented as a set of skills. An agent hence has to master a set of skills in order to generate a particular innovation. The authors proceed by generating a Global Innovation List (GIL) consisting of a subset of incremental and a subset of radical innovations. Incremental innovations are constructed from an innovation already in the GIL by adding a single skill to it, while radical innovations consist of skills not already used in innovations in the GIL. If a particular agent or group of agents in collaboration generates an innovation, this will be recorded as a tag placed on the innovation in the GIL. Another agent or group of agents can then no longer create that innovation.

Each period of the simulation ('cycle'), agents get a turn in random order. Each of the agents then goes through an individual learning phase during which R&D is conducted to possibly generate an innovation and a partnering phase during which potential partners are sought and interacted with to carry out a joint innovation.
At agent level, each agent is endowed with a Skill Profile (SP) and a list of acquaintances. The SP contains a fixed number of active skills and a variable number of dormant skills. The SP can be expanded by individual learning and by interactive learning if two agents collaboratively generate an innovation. Throughout the simulation, agents will try to form innovations using the active skills in the SP by comparing the skills available to those required to generate an innovation present in the GIL (an agent hence knows what it has to learn!). If an agent is able to produce an innovation, it will do so. Otherwise, it will proceed to learn particular skills that are required otherwise.
Learning is modeled as performing a depth-first search on the FSU starting from skills already in the SP. Such a 'child node' can only be mastered if all of its parents are in the SP, i.e. some skills develop from a recombination of multiple, more basic skills. Hereby, the agent is also able to go down one level in an attempt to master other parents required. The authors furthermore distinguish small, medium and large firms dependent on the number of skills they can master per cycle, to meet the fact that larger firms generally have bigger R&D departments and are hence able to handle a wider spectrum of skills. This process obviously models 'individual learning'.
If an agent gets stuck, an agent can depart from this solo innovation process, pick an innovation from the GIL of which it has already mastered some skills and look for a partner to collaborate with. The principal agent will contact agents in its neighborhood to see whether they are able to generate the innovation if they combine their SPs. If they succeed, they both innovate and acquire the complementary skills that were required. This obviously models 'learning through interaction'. If an agent is not able to find such a partner, the search terminates. The authors have incorporated a structure to create intermediate links, but they have not involved that in the study at hand.
As mentioned, the paper lacks results of rigorous testing of the model. The authors however already discovered that solo innovation is rare and the propensity to collaborate increases if they increase the neighborhood size.

In anticipation of the detailed description of the NK landscape in the subsequent section, two models of collaborative search on such a landscape are discussed here. It is assumed that the reader is to some extent acquainted with the concept of the NK landscape. Hereby, N is the number of elements spanning a landscape and K the number of other elements each elements affects. We will provide a thorough definition of the NK landscape in section 5.2 and provide an overview of basic properties of the NK landscape in subsection 3.2.2. For the paragraph ahead it is important to understand that an adaptive walk is the same as hill-climbing. This is a process in which all local mutations of a focal point are evaluated and the most fit one is selected as new focal point. As soon as there is no improvement possible, the adaptive walk has found the local optimum. It is furthermore important to understand that a patch simply is a subset of the N elements to which such an adaptive walk is confined.
Kauffman and Macready (1995) transformed the NK landscape to form a square lattice where the fitness of a particular node is affected by each of its neighbors[2]. They investigated the consequences of breaking this system into "selfishly co-evolving patches". Kauffman and Macready (See 1995, p.38): "As K increases and the lattice harbors more conflicting constraints, better [high fitness] states are found first by [maximizing][3] on the entire lattice; then suddenly, optimal behavior requires partitioning the system into independently and selfishly optimizing departments!". In our context, this translates to that one can -by choosing the appropriate patch size- have the system

2. If $K = 4$, the fitness of a node is affected by the state of the neighbors just north, east, south, west of it. If $K = 8$, also the state of the neighbors just NE, SE, SW, NW affect its fitness. Et cetera.
3. Changes made to meet the current interpretation: we maximize fitness while they minimize energy in a system of spin glasses.

	Cowan et al. (2004)	Kauffman and Macready (1995) Frenken and Valente (2003)	Taylor and Morone (2005)
Subject	Network properties	Effects of decentralization on search performance	Partnering propensity
Technology	Knowledge vector	Binary landscape string	Set of (active) skills
Innovation	(Only by collaborating)	(Only by collaborating)	Search of skill space to produce known innovation.
Coll. R&D	Cross-fertilization of knowledge vectors	Hill-climbing own patch of joint solution	Exchange of skills & innovating together
Coll. options	(No options)	(No options)	Try solo, but on failure try bilaterally.
Coll. criterion	Attractiveness of partner: Expected 'amount of knowledge' that will be produced	(Not optional)	Attractiveness of partner: Skill complementarity
Main indep. var.	Task separability θ Weight of past experience α	Landscape complexity K Patch size P	Properties of skill space and innovation list

Table 3.2: Fundamental Models of R&D collaboration

as a whole escape poor local optima in which it would otherwise get stuck.
If we conceive R&D as an adaptive walk on the patch, it becomes immediately clear that by associating each patch with a single agent, we are actually looking at an abstract model of collaborative R&D.
Frenken and Valente (2003) further investigated this observation. The authors also divide the landscape (not necessarily reformed into a lattice) into a number of patches. Where the conventional adaptive walk moves to a new location if the mean fitness of elements belonging to a patch increases, Pareto search moves to a new patch only if in addition none of the fitness values of the individual elements is decreased. It is argued the optimal patch size definitely is between one and N. They confirm findings of Kauffman and Macready (1995) that it is beneficial to reduce the patch size for conventional search. Especially for moderate to high K, relatively poor optima are escaped. Simulations show that with Pareto search the number of local optima increases exponentially, but that with an increase in patch size, the fitness of the obtained optimum drops to 0.5 fast. Regretfully, the authors have not included findings for the number of moves made (or mutations considered) until the local optimum is reached.
These findings have obvious implications for Management Science. Several scholars have produced interesting articles in which they have embraced the Complexity Theory to derive strategy recommendations (See e.g. McCarthy, 2004; Fleming and Sørenson, 2003; Anderson, 1999).

3.1.3 Evaluation

Here we will evaluate the differences and similarities of the models in both categories. Eventually we will evaluate the extent to which particular elements are suitable for inclusion in our own model and whether and, if so, how we have to adjust and/ or improve elements if we are to use them in our own model. We will thereby of course also consider the features we need to support operationalizing our conceptual TCE model.

Let us first discuss the Neo-Schumpeterian models of R&D collaboration. After a (non-exhaustive) survey of the literature at hand, there are, surprising enough, only a few models that address R&D collaboration in a genuinely Neo-Schumpeterian setting (or a serious attempt to meet the prerequisites). In both Neo-Schumpeterian models of R&D collaboration, the research subject is the development of R&D networks over time. To that end, agents can endogenously 'decide' to (under particular preconditions) connect or disconnect from other agents.
In both models, technology is represented as a capability vector, but where a firm is associated with

a single vector in the Zirulia model, Gilbert et al. in fact allow the agent to maintain a whole set of capabilities. In the Zirulia model, technological improvement is achieved by collaboration only, which brings about a displacement in the capability space. In the Gilbert et al. model, technological improvement is some operation on KENEs related to activities, e.g. cross-breeding of some kind in case of bilateral or network innovation, learning and forgetting in case of solo innovation, where innovation can be either of incremental or radical nature.

In fact, in the Zirulià model, R&D options are either complete idleness or bilateral capability displacement, while in the Gilbert et al. model, the options are as just described. The Gilbert et al. model is praised for its rich set of actions and options allowing for sophisticated agent behavior, free of extreme stylizations.

The Zirulia model does not have an explicitly selection device incorporated. If the Cournot game suggests a production of zero, the agent is removed. In the Gilbert et al. model, the selection device is much more realistic. Agents 'exit' due to ordinary bankruptcy if the agent runs out of credits. Agents use credits for innovation and collaboration, and replenish capital stock from payoff from the Oracle based on 'fitness' of the innovation hypothesis.

Both models obviously have technological improvement, but when it comes to evolution of R&D heuristics, none of the models has endogenous sources of novelty! The models do not have entry or imitation! Especially in the Gilbert et al. model this to be considered a serious flaw, as the authors after all have the aspiration to 'reenact' existing instances of industry development.

In both models, the industrial dynamics takes the form of progression of the technology frontier. Schumpeterian innovation in fact is embodied in the improvement of the capabilities, not in the R&D heuristics.

These findings are summed (with technical details) in table 3.1.

Let us now discuss the fundamental models of R&D collaboration. There are many models falling in this category and we have selected only a few. As this category also is less restrictive and as it is far easier to establish such less comprehensive models, the fundamental models differ greatly in their basic design. Where Cowan et al. focus on (again) network properties, Taylor & Morone focus on partnering propensity, while the authors of the NK landscape related studies typically study the effect of decentralization on search performance.

Also the codification and conception of technology differs greatly. Cowan et al. and Taylor & Morone conceive technology as a vector of knowledge or skills, while technology in an NK landscape simply is a configuration of elements (where an element can well stand for particular knowledge or cognitions). The behavioral options in these models are highly restricted and agents follow the same straightforward heuristics. The same goes for innovation. In the Cowan et al. model, the agents are 'matched' (based on past experience) and simply cross-fertilize the knowledge vectors. The agents do not have an option to, e.g., develop knowledge solo. In the Taylor & Morone model, agents first seek skills solo, and if that fails, they will exchange skills with the most suitable candidate. In the NK models, there is no activity whatsoever, but each agent simply optimizes its patch following an adaptive walk and thereby changes its contribution to the jointly optimized technology. This actually comes close to what decentralized combinatorial optimization models do (See e.g. Vidal, 2004). What makes these fundamental models particularly attractive is the use of a very small number of independent variables to study the actual 'search behavior'.

The findings are summed in detail in table 3.2.

We now discuss the extent to which either a complete model and/ or elements of these models might be suitable to be used in our own model. For starters, it is concluded that none of the models is in its entirety suitable for our purposes. As we are aiming for pure experimental research, we do want the basic framework to expose independent variables that are operationalizations of the factors in the adorned TCE model. Not surprisingly, we see that none of the models at hand offers that. We furthermore also want variations of those independent variables to have as tractable and transparent

as possible effect on collaboration behavior. We should thus limit the behavioral options! In that respect we are leaning toward the fundamental models more than to the comprehensive models that are simply used to get some impression of dynamics and network features.
Apart from exposing operationalizations of the conceptual factors, we also need to have a micro-level definition of R&D, collaborative R&D and agent matching (i.e. finding of a collaborator). Both R&D and collaborative R&D strongly relate to the conception and encoding of technology, and we have found that they differ a great deal from model to model. We think of (collaborative) R&D as technology landscape search. As we belief this topic is worth special attention, we have decided to dedicate a whole section to something called technology landscapes search models. We will then also evaluate the extent to which these technology landscape search models can be expanded to model R&D *collaboration*.
Our conceptual model is predominantly designed for meso-level inferences, so there now still is some lacuna as far as agent matching goes. While the fundamental models have a top-down agent matching mechanism which is as good as rational, the matching in the comprehensive models really stems from individual 'preferences' and experiences. Although we might prefer the latter, we have to be aware that there is a trade-off between transparency (and unambiguity) and descriptiveness (also see chapter 4 on model design in this respect), and since we still are geared toward discerning causal relationships, we again opt for reservation in adding parameters.
Recall that we not only have to operationalize the TCE model, but that this TCE model is framed in the Neo-Schumpeterian evolutionary framework that allows us to have collaboration (genuinely) emerge endogenously. As such, we need an evolutionary mechanism to condition the population of collaboration strategies and -as a consequence- we will have to make collaboration *optional* like in the Gilbert et al. model. On the one hand, the fundamental models have no evolutionary framework at all and in the -what we take to be the- Neo-Schumpeterian models (the Gilbert et al. and Zirulia models) the evolutionary framework is defective! Unlike these models, we will definitely implement endogenous exit, entry and mutation of strategy instances.

3.2 Technology landscape search models

We will first introduce the topic of technology landscape search models from which we conclude we have to discuss both so-called fitness landscapes and so-called opportunity landscapes. We will subsequently provide a short overview of such landscape search models. Eventually, we will evaluate the (difference in) properties of the various landscapes and assess their value for our own research purposes.

3.2.1 Introduction

As we have seen, Neo-Schumpeterian researchers introduce technology landscape search in their Neo-Schumpeterian models to represent the R&D activities of firms. At the level of a single firm, R&D comprises, on the one hand, strategic decisions (e.g. which direction to pursue, whether to imitate or explore, or whether to collaborate or work solo), and, on the other hand, the actual operational search for new technology in terms of experimenting and recombining. This section is concerned with such operational search models.
We want to know -at a meta-level- why researchers use a landscape search model. We are of course interested in what such a technology landscape search model exactly is, and why a metaphor for R&D is used and how it is used. We will answer these questions first. We are furthermore interested in the various components making up the landscape and differences in these components in various landscape search models. We subsequently discern several types of models and opt to investigate two types.

3.2.1.1 *Meta-level*

First of all, why use a search model metaphor in the first place? At the outset of this field of Neo-Schumpeterian Economics, Winter (1984) stresses that formulating the 'search model' is "an attempt at representation of the cognitive processes typical of some identifiable group of 'searchers' in a particular economic context, and would thus incorporate much of the factual background of that context.". According to Winter it is important to realize that regardless of whatever the economic and technological outcomes of search are, "the real action is at the level of ideas and skills". This can "be helpful in arriving at hypotheses regarding the structure or attributes of the search process".
Does this mean that we therefore have to have a detailed representation of R&D? Not quite, rather than devising a detailed, comprehensive and adequate white box model of the actual search process, it is important to have the search model reflect the properties of the actual R&D process as far as they affect the economic performance of the agent. Bart Verspagen argues that the single most important feature of this search process is the fact that the path and final outcome are unknown, i.e. that there is technological uncertainty. According to Simon, such *technological uncertainty* in R&D is ultimately captured by a process of trial-and-error in which the agent does not know or is not able to reason about the direction and path to pursue to optimize final outcome.

What then is studied with technology landscape search models? We cannot answer that immediately. As we just saw, the search model is a device to introduce technological uncertainty in operational process models of innovation. There however is more. Frenken (2005, p.8) hinted on a tendency toward focusing on the model of technological development and moving away from studying models of competition between firms with different technologies. Researchers more and more want to know the effects of particular features of technology (possibly as a source of technological uncertainty) on emergent behavior. In some cases, this even is the sole purpose of the study. We will later describe various technology landscape search models and then hint on what is studied with them.

3.2.1.2 *Landscape search model features*

We will now first introduce three dimensions making up a technology landscape, we will then hint on how landscapes can be used in research, and, finally, provide a detailed decomposition of features of these components. This allows us to describe the essential issues of each landscape search model. We will use this decomposition to isolate three classes of models and describe the models in each of those classes in more detail.

First of all, as said, we distinguish three dimensions of a landscape search model: (a) that what is searched for (the technology) and thus spans what is explored (the landscape), (b) how the agent is searching (search heuristics) and (c) how the landscape properties are manipulated.
Let us now discuss each of these three dimensions. Ad (a), the agent searches for technology and we hence refer to this dimension as the 'conception of technology' of a landscape search model. In these models, there -grosso modo- are only three conceptions of technology. One, technology conceived as a set of capabilities or routines, or vector of knowledge concerning activities other than R&D. Two, technology conceived as an *instance* of technology or technological knowledge. Three, technology conceived as production efficiency (capital labor ratio).
Ad (b), the agent searches using rules-of-thumb and heuristics and we hence refer to this dimension as the 'conception of innovation/ search' of a landscape search model. The actual search heuristics either moves the agent from one capability set or production efficiency to another or either yields new instances of technology which are stored in a repository of instances. In the first case, an agent typically has a 'location' on the landscape. In the second case, agents typically control a set of technology instances and can, for example, bring those to the market or recombine and exchange

those technology instances. It is also well possible an agent has an own 'strategy' in terms of a set of specific parameters that control the way the agent searches.
Ad (c), the landscape usually has features controlled by the researcher (and not through some endogenous mechanism) that are used to affect the search process. We refer to this as the 'experimentation landscape features'. These features usually relate to the actual research subject of the study. One typically has to distinguish the feature of the landscape, how this feature is controlled (often by means of a particular variable that either is or is not exposed in the model) and how this affects the search behavior of an agent.

Second of all, we see that such technology landscape search models are used in various ways in the studies inspected. Some authors conceive technology as a structure of knowledge and study the effect of the 'topology' of knowledge elements on the performance of various types of search strategies. Others conceive technology as a constellation of elements and study the effect of 'interdependency' on the performance of particular recombination strategies. Yet others see a technology landscape simply as a range of isolated opportunities to invest in, to study the effects of cost and benefits on moving and investment behavior.
If the technology landscape search is not purely for fundamental research but tied to an evolutionary framework to study emergent behavior, the model should shed means to introduce selection. This can be done by endowing a search trail and a technology instance found with ordinal features expressing the efforts required to discover a particular technology instance and the relative value of this instance over another. By associating these ordinal features with costs and payoff, the core search process is connected to an economic reality. It is then easy to establish a selection device, e.g. a market.

Third of all, now that we know the basic dimensions and have seen some materializations of these dimensions, we can zoom now in on each of the three dimensions of a landscape search model distinguished earlier: the conception of technology, conception of search and landscape manipulation. We thereby provide a mean to dissect a landscape search model and as such allow classifying technology landscape search models. If possible, we will refer to a simple example in which agents search a 2D space of capital and labor quantities looking for a capital-labor ratio (process technology specification) with a higher process efficiency.
Firstly, we describe the subdimensions of our conception of technology as that is what is searched for. Each model has a particular codification/ representation of technology (e.g. single ratio of capital and labor) and it closely relates to what technology represents of the agent (e.g. its process technology specification or capability). Depending on the conception of technology, it is a single feature of the agent (like with process technology specification) or the agent can have multiple technologies (e.g. products) stored in a technology repository. The model also has to specify the top-down imposed technology structure. An example of such a technology structure is 'cumulation' which can mean that leaps in the capital-labor space are not possible but that improvements cumulate, or that low-level technologies have to be invented before high-end technologies can be developed.
Secondly, we will describe the subdimensions of our conception of search. We already distinguished the operational R&D model and the R&D strategy during the description of the agent heuristics in 2.2, and these heuristics are in fact both contained in the landscape search model. The operational search heuristic can be e.g. local displacement of the capital-labor ratio, while the more high-end search strategy heuristic tells the agent when and what to pursue, e.g. generate a random ratio by means of invention. If the technology landscape search model is employed in a Neo-Schumpeterian setting, the variation in strategies is crucial as it constitutes the factor 'variance' in the evolutionary framework.
Following from earlier expositions, the landscape search model has elements that introduce uncertainty in the outcome of search (e.g. the local displacement is Gaussian). Note that there can also

be properties or capabilities of individual agents that constitute this uncertainty. Such capabilities or properties usually affect the search heuristics (e.g. the actual standard deviation of local displacement, the search radius, et cetera), but can also form accidental (dis)advantages that play a role (e.g. initial location in capital-labor space).
In order to hook up the landscape search model in an evolutionary framework, we are interested whether a model already has or at least allows for implementation of a search costs versus returns measure. This would allow selection based on search efficiency. Most researchers implement means to measure performances of individual agents (apart from the researchers that are primarily interested in manifestations at an aggregate level that have no direct need for micro-level measures) which would allow selection on the basis of performance. Mind you that 'search costs' can also be accounted for by limitation of search capacities and thereby reflect in performance, e.g. small firms (with limited resources) can do only one step (as it otherwise gets to costly), while large firms can do two because they have more resources.
Thirdly, the dimension of experimentation landscape features is specific for each landscape and is, as said before, closely related to the subject under study. A factor in the conceptual model under study is defined in operational landscape variables. Such an operational parameter is then tuned to study to the effects on the performance of search.

We now have obtained the following detailed decomposition of landscape search model features:

- Conception of technology
  - Codification/ representation of technology (e.g. capital labor ratio)
  - Technology is single capability or an instance stored in a whole repository?
  - High-end imposed technology structure (e.g. cumulation)
- Conception of innovation/ search
  - Operational search heuristic (e.g. random local displacement or structured progression)
  - Strategic search heuristic (e.g. imitate, radical or incremental innovation)
  - Incorporation of technological uncertainty outcome (e.g. displacement is Gaussian)
  - Capabilities/properties that affect performance of agents (e.g. initial ratio)
  - If and -if so- how cost and performance can be measured, so as to be able to (possibly) integrate a selection device (e.g. costs of a draw versus returns from marketing)
- Low-level experimentation landscape features
  - Actual feature, the parameter to tune the feature and the effect it has on the search process and outcome (e.g. concave object function/ concavity parameter, acceleration then slowing down)

We will use this as a sort of 'assessment framework' later on.

3.2.1.3 Types of models

There are almost as many representations of innovation as there are Neo-Schumpeterian models, yet, based on the dimensions discerned, there are three categories: Firstly, the traditional, low to moderate dimensional production function parameter landscapes. The Nelson & Winter search models belong to this category. Despite Winter's plea for a gray box model of search, their search simply boils down to a random local displacement (with mean 0) on the production function parameter space. The outcome of innovation is uncertain, and in expectation yields no improvement at all.
Secondly, there are so-called fitness landscapes, either two- or multidimensional. The distinction with the first class is merely conceptual. Technology rather is a constellation of elements with some performance/ fitness. The landscape however has an explicit 'ruggedness' parameter strongly affecting operational and indirectly strategic search behavior.
Thirdly, there is a class of miscellaneous 'opportunity landscapes' pictured as a two-dimensional

grid where each cell (or node) in this grid represents a technology with a particular state (e.g. undiscovered, invented, developed into innovation, exploited, dominant et cetera). The search model is more on the strategic than on the operational side.

The models in the first category are firmly rooted in mathematical Neo-Classical models and therefore are more econometric in nature then they are conceptually abstract and comprehensive (See Andersen et al., 1996; Winter, 1984). Despite the laudable system of equations allowing for introducing price-setting behavior, financial involvement of third parties, et cetera, Nelson & Winter models generally reduce technological progress to *process* innovation and imitation by means of pure shifts in productivity and capital coefficient. When zooming in on the actual R&D process, technological change hence is relocation on a simple two-dimensional capital-labor parameter landscape.

Recent Neo-Schumpeterian models, especially those aiming for a fundamental understanding of the dynamics, rather look for a conceptually comprehensive description of the actual R&D process. We therefore decide to look at the two other types of landscape search models. We will first discuss several models in both classes (which is only a small selection of models around) and only then evaluate them within our just introduced assessment framework.

3.2.2 Fitness landscapes

We will discuss, in essence, only two fitness landscape search models:

- Again the Kauffman NK landscape model, but now focusing on fundamental properties as produced by Koen Frenken (in multiple papers) and by Stuart Kauffman, Jose Lobo and William Macready.
- And a model by Gino Cattani and Sidney Winter concerning search on a fractal landscape.

An attractive, seminal technology landscape is the so-called NK fitness landscapes Kauffman (1993, p.40). Variable N refers to the number of elements in a system. As Frenken (2001) made clear, the landscape 'string', i.e. the array of elements, can represent with a mixture of product features, business process techniques, service elements, marketing channels employed, et cetera. The fitness of a single element is determined by its own state as well as the state of K other elements. Substituting or removing particular elements does in many practical situations indeed lead to malfunctioning or even improvement of the whole system. Given the background of Kauffman, this K is referred to -in terms of genetics- the richness of epistatic interactions. Each element (locus) can take A states (allele). This framework allows mapping types of actual technological elements to allele and thus describing the technology universe and studying the actual deployment (See Frenken, 2001; Frenken and Nuvolari, 2003).

Here, this K is referred to the complexity of the system and in most cases $A = 2$, such that each element has a binary state space $\{0, 1\}$. The number of possible strings then obviously is 2^N. Each string has a particular fitness, being the average of the fitness of the individual elements. As mentioned, the fitness of an individual element is affected by the state of K other elements as well. If K equals zero, it is possible to simply reset each element to the state with the highest fitness. This corresponds to single-peaked and smooth fitness landscape. As changing the state of a single element affects -on average- the fitness of K other elements, increasing K causes the fitness landscape to become increasingly 'rugged' with an increasing number of peaks. If $K = N - 1$, the state of each element affects the fitness of all elements, which corresponds to a -what Kauffman calls- fully random fitness landscape.

Let us denote a landscape string with T and its fitness as $F(T)$, whereby $F(T) : \mathbb{B}^N \rightarrow [0, 1]$, by convention the fitness of a single element is drawn from a standard uniform distribution. The Hamming distance $H(T_1, T_2)$ between to landscape strings T_1 and T_2, which measures the number of differences in states of two strings (i.e. $\sum_{i=1}^{N} |T_1[i] - T_2[i]|$). An m-neighbor is a string with a

Hamming distance of m, -depending on the definition- exactly or at most. An adaptive move from an arbitrary string is conceived as moving the focus from the current (focal) string T_f to the m-neighbor string with the highest fitness $F(T_n)$. If a string T has no m-neighbor string with higher fitness, the string is called a (local) optimum. An adaptive (m-step) walk starting from an arbitrary string T_1 is then a sequence of moves until the optimum T_L is reached. If the walk visits strings $T_2, T_3, \ldots, T_L$ then $F(T_1) \leq F(T_2) \leq \ldots \leq F(T_L)$.
In this paragraph, some results found in Kauffman (1993) will be summed. If complexity K increases, the length L of such a walk and the number of 'mutants' inspected along the walk decreases. By convention, the walk from T_1 is said to be 'attracted' to the particular optimum T_L. The whole collection of strings that are attracted to optimum T_L is called the basin of attraction of T_L (See p.176 Kauffman, 1993). For low K, the highest optima have the biggest basins. Furthermore, high optima are located close to each other. If K increases, ceteris paribus, the mean fitness of local optima first increases, reaches a peak around $K \approx 3$ and then decreases. Although the mean and supremum of the optima decreases, the variance of the heights of the optima increases. If K increases, ceteris paribus, the mean walk lengths to local optima decreases.

Following Auerswald & Lobo, Kauffman et al. (2000) model a firm's quest for technological improvement as exploring the fitness landscape for optima. Hereby a landscape string is associated with a production recipe with N elements. Each element has S alleles and there are e intranalities (i.e. the number of epistatic relationships previously denoted with K). The authors investigate the optimal Hamming distance to search for production recipes that are more efficient (fit), thereby bearing in mind that moving further away is more costly. As becomes clear from their figure 4 and 5 (See p161,162 of Kauffman et al., 2000), that the optimal search distance increases with decreasing efficiency and with decreasing search costs, especially for high correlation coefficients.
These findings should not come as a surprise, though. If the correlation coefficient is high, high peaks are correlated, hence if the firm is in a poor optimum (low efficiency), the chances look slim that the firm will find high peaks (high efficiency) nearby. Therefore the firm should best look far away for a new recipe, where the distance typically depends on the actual costs.
A warning is issued. In Neo-Schumpeterian models, search procedures employed by firms usually are simple heuristics to reflect the bounded rationality. Although open to debate, a Neo-Schumpeterian firm does not have (a proxy of) the landscape correlation coefficient or perhaps even a measure of own efficiency at its disposal. On the other hand, if the firms in a Neo-Schumpeterian model are equipped with a mechanism to resort to radical innovation if incremental innovation proves to be insufficient, one would allow the firms to at least partially meet the aforementioned strategy.

Cattani and Winter (2004) conceive a fitness landscape as a two-dimensional terrain over which firms search for peaks. Hereby the fitness is associated with performance of the firm. They actually use a random midpoint-displacement algorithm to generate a mountainous terrain on a lattice. It is possible to tune the ruggedness of the terrain using a single parameter. The authors randomly assign firms to positions on (a confined subregion of) the landscape and provide each of them with a direction in which the agent will search the landscape. The fitness of the point at which a firm is situated translates in the payoff it receives. There however is a threshold below which the fitness is too low and "even a monopolist [is not able to] find a buyer". If an agent finds itself at this 'sea-level', there is no market feedback to guide search. This concords with the uncertainty during early industrial life-cycle phases.
Although it is a far cousin, the fractal landscape differs essentially from the NK landscape. Two advantages are the convenient visualization of the landscape, as well as the ease with which the landscape can be deformed e.g. tilted. The authors themselves however already conclude that they have lost the property that ruggedness of the terrain is caused by the complexity of interactions of elements. They however argue that with construction of a landscape using the midpoint-displacement algorithm, the terrain is formed by layers of decisions. So, the ruggedness hence is caused by many

detailed decisions.
Agents however not bluntly seek in one direction, but have an angle of directions they investigate and also react to market feedback. The market feedback is in the form of payoff based on the fitness and the intensity of competition and a convex industry revenue model. Agent i has a particular inclination ν_i toward persisting in the direction preference and being guided by fitness. If $\nu_i = 1$, the agent i persists searching in the predefined direction, if $\nu_i = 0$, will respond to market feedback only making the agent a pure hill-climber. Depending on the shape of the peak (sharp versus rounded), an agent will search beyond rather than staying put at the peak for some (high) value of ν_i.

3.2.3 Opportunity landscapes

This list of landscape search models in this class is certainly not exhaustive, but due to the limited time, we have decided to discuss just three models:

- An exploration/ exploitation model by Giorgio Fagiolo and Giovanni Dosi.
- A percolation model by Jerry Silverberg and Bart Verspagen allowing for reproduction of a great many stylized facts.
- A quick remark on the aforementioned model by Richard Taylor and Piergiuseppe Morone.

Fagiolo and Dosi (2003) devised an attractive metaphor for R&D consisting of exploration, imitation and exploitation. Here, only a short description of the 'technology landscape' will be given. The technology landscape consists of a two dimensional lattice ('sea') containing technologies ('islands') and agents can either utilize the technology ('exploit the island') or innovate ('float around' until hitting another island). The productivity of new technology depends on the location related to known technologies as well as the best practice skills of the agent in question. Each exploited technology has a certain attractiveness that tempts other agents to imitate this technology. This is modeled by having each agent broadcast the productivity of its technology that is instantaneously received by all other agents. The 'attractiveness' not only depends on the productivity but also dissipates with distance between the sender and receiver. If any of the technology attractiveness signals is sufficiently strong, an agent decides to pursue imitation by moving toward the island one step at a time.

Silverberg and Verspagen (2002, 2005) model R&D as search on a percolation landscape with a cylindrical form. Starting from the baseline at the bottom, R&D search is modeled as investigating sites within a predefined radius at random. The state of a particular site is defined to reflect that of a technology instance with which the site is associated (e.g. undiscovered, discovered but unviable, viable). To introduce knowledge accumulation, a discovered site still has to be made viable by connecting it to the baseline. By establishing such a technology 'chain', an invention becomes an innovation.
In a more advanced setting, they associate the innovation locations with payoff being disbursed and endow a firm with an investment strategy to have the firm determine what to invest in investigating the sites in its vicinity. There are particular (stochastic) costs involved in discovering a particular technology, and the economic problem obviously concerns how much to invest. In addition, a firm repositions itself on the lattice based on the 'best-practice frontier' of the column, which causes agents to be drawn to particular regions (and there hence is a process of 'self-organization' of the industry) yielding a high population density at certain locations.

The Taylor and Morone (2005) model has already been discussed in the previous section, so this paragraph will be limited to a short remark on the R&D search model. The authors assume innovation to take place if the necessary skills are mastered. Agents are able to scan the list of possible innovations (which is generated at startup and does not change along the way) to determine a yet undiscovered innovation to pursue. An agent will typically select the innovation for which it has the most skills mastered already. As such, R&D search is modeled as exploring the skill universe.

This skill universe takes the form of a 'river delta' directed tree of basic and more advanced skills. A particular child node can -by construction- have multiple parents. To master an advanced skill (child node), all basic skills (parent nodes) have to be mastered. Each advanced skill hence is mastered once it is connected to the root node over all possible paths involving required ancestor nodes. This nicely captures the cumulative nature of learning.

3.2.4 Evaluation and assessment

Evaluation of landscape search models

We will not evaluate all landscape search models, but restrict ourselves to three opportunity landscapes and three fitness landscapes. Using the preceding description of the technology landscapes, we have established table 3.3 in a straightforward exercise of filling out the framework given in 3.2.1. We will use this overview for our evaluation.
Firstly, as far as the conception of technology goes, we see that technology is mostly seen as the capability of an agent in the form of a two- or multidimensional vector. Only in case of Gilbert et al. and Taylor & Morone, we see that technology is an instance that is stored in a repository. It must be said that it is just a matter of choice as we can easily change the use of the technology from a capability into an instance and the other way around. We see that, in most landscape search models, there is a high-end imposed structure of accumulation of technology. In both the opportunity and fitness landscapes, it generally takes the form of a progressive innovation trajectory in which agents gradually improve the technology or technological performance.
Secondly, the conception of innovation generally strongly relates to the basic design of the technology landscape. We however see that fitness landscapes generally have more operational search heuristics, while the opportunity landscapes have more strategic search heuristics. The emphasis in lattice opportunity landscapes is on decisions like 'imitate' or 'explore' as the operational activities generally are somewhat more limited. It is noted that it is possible to expand the fundamental fitness landscapes to have agents also follow more strategic search heuristics if we define the common economic environment in which these agents operate. In most opportunity landscape models, this has already been defined.
Technological uncertainty generally is introduced by limited foresight in the consequences of actions. In opportunity landscapes, we see that actions like imitation (on the basis of communicated attractiveness of certain technology) is a powerful strategy to overcome technological uncertainty.
The inherent capabilities of the agent that affect search performance generally are the initial location and -in case of the opportunity landscapes- action options of the agent. We again see that if we would further define the economic environment in the more fundamental fitness landscapes, we would also be able to introduce additional search capabilities (options/ limitations).
The last subdimension of the conception of innovation in the landscape search model is presence of a cost/ payoff model (or effort/ performance) which would allow us to hook the landscape search model into a selection device. We do see that the KENE search model of Gilbert et al. does have such a cost/ benefit structure, but this of course is related to the fact that it already is in a Neo-Schumpeterian framework. Also the Silverberg & Verspagen model has research costs versus payoff when discovering technology. The other landscapes do not (explicitly) have such a cost/ benefit structure, but in most cases it is quite easy to associate the fitness or attractiveness of the technology with the payoff and some property of the search trial with the expenditures. The Taylor & Morone technology landscape is an odd model here as it does not have costs but rather limitations of search capabilities.
Thirdly, the experimentation landscape features really strongly relate to the goal of the study. It however is remarkable that the opportunity landscape generally have no parameters exposed explicitly. Then again, these opportunity landscapes are used more to generate ideas on the regularities that might emerge, rather than testing hypothesis. The fitness landscapes generally have one or

more parameters exposed that allow the researcher to tune the ruggedness of the landscape and thereby affect the search performance.

Requirements for our search model and assessment of the landscape search models

Let us now zoom out from the detailed evaluation of the technology landscape features and map them onto the search model features required for operationally defining the envisioned comprehensive Neo-Schumpeterian model. Let us start off with the four core components discerned in section 2.2 and specify the actual requirements our landscape search model has to meet. First of all, the constellation of agents models a sector of firms that conduct R&D solo or in collaboration. Second of all, the entrepreneurial heuristics should hence encompass operational landscape search as well as facilitate an R&D strategy deciding whether or not the agent must collaborate. The suffering of bounded rationality generally reflects in these operational and strategic landscape search heuristics. As mentioned in 2.2, the heuristics are also there to cope with the economic environment in which the agents operate. The economic environment obviously closely relates to the meso-level, sectoral conditions that affect the collaboration propensity according to our TCE model. Third of all, the Neo-Schumpeterian model requires a market as evolutionary selection device. To that end, we need to be able to order technology landscape search performance and search outcome and, as such, to connect it to a cost/ benefit structure facilitating simulation of a market. Fourth of all, we would ideally want the Neo-Schumpeterian model to allow genuine industrial dynamics. As we have seen, we find ourselves doing experiments to test hypotheses, so, we, first and foremost, focus on facilitating that rather than reenacting strands of industrial developments. In sum, we primarily want the technology landscape search model to:

- Expose variables we can use in operationally defining the adorned TCE model.
- Allow collaborative (or at least iterative) rather than purely soloist search. Search should reflect Simonian capability restriction.
- Facilitate an ordinal cost/ benefit structure of search and search outcome that allows us to construct a selection device.

Let us now use these three issues to assess the technology landscapes discussed. The user is advised to look up the properties of the landscape search models in the tables provided in this chapter.
Firstly, let us assess the extent to which these landscapes facilitate operationalization of TCE factors complexity, complementarity, appropriability and level of competition.
Appropriability is to be implemented by either preventing 'leaking' technology or technological knowledge to other agents, or by preventing or hampering the receiving agent to put it to use. To allow spillover, we have to look at how technology is codified and what it represents. Due to the level of abstraction, technology can be associated with product-process combinations in all models. In the technology landscape search models there is just one single technology codification, namely, as string, but with different dimensions. The Taylor & Morone and the Gilbert et al. models do utilize a 'technology component' repository, while in the other models, a firm is completely associated with its capability. Spillover can be conveniently modeled as loosing instructions how to produce (components of) a (family of) technology instances. If we model technology as a capability vector, the receiving agent can profit from this knowledge and hence gains an increase in performance. If we model technology as a configuration, the receiving agent can simply also reap the benefit from putting that configuration to use (in whatever manner that is in the model). So, clearly, incorporating spillover is no problem.
Operationalization of appropriability is easy in instance landscapes as technology is uniquely identifiable. It is therefore easy to block (part of the payoff) being disbursed to anyone other than the inventor. In capability models, appropriability is somewhat more difficult as the capabilities are linked immediately to payoff. There is no evident mechanism with a real-world counterpart to attribute part of the payoff to the agent benefiting from the incoming spillover to the agent from

which the spillover originates.
Most of the models discussed do not allow an immediate conception of *complementarity.* The Gilbert et al. and Taylor & Morone model, the complementarity is in terms of addition skills or (other) KENEs. In decentralized search in NK landscape models, complementarity is in terms of additional capabilities, namely the control over particular elements out of reach for other 'agents'. Coincidentally, only the Taylor & Morone and the Gilbert et al. search models have already been used in a model with (some form of) collaboration. Of the other models, only the NK landscape has features that immediately facilitates cooperation in operational search, after all, various authors have already studied decentralized search (see 3.1.2) albeit in a fundamental setting. For the other models, one would have to devise this completely from ground up. We can introduce complementarity of knowledge as sharing landscape information (e.g. sharing of information on altitude, attractive islands or cell-state maps) and complementarity of capabilities as iterative search-and-jump of agents controlling different patches.
As far as the factor *level of competition* goes, the technology landscapes should hence facilitate an ordinal cost/ benefit structure that allows for ordering the performance of agents. We already discussed this.
Operationally defining the concept of *technological complexity* finds its origin in the underlying structure of the search problem. In the opportunity search models, the challenge of search is the uncertain distribution of opportunities or the cost/ benefit structure, where complexity lies in the difficulty of finding opportunities. In the fractal fitness landscape, the complexity resides in taking a series of suitable, cumulating decisions. In the Gilbert et al. landscape (as well as other capability models like that of Zirulia and Cowan et al.), the complexity lies in the uncertainty of the outcome of capability extensions. In the fitness search models, the complexity resides in finding a suitable constellation of elements given the underlying interdependencies of elements. Note that the complexity of search in the fitness landscape closely meets the narrow conception of complexity defined in section 1.3! We can tune the number of interdependencies, i.e. the technological intricacy, by changing the parameter K. Clearly, the operationalization of complexity in the fitness landscape is by far the closest to what we want.

Secondly, let us assess the extent to which these landscapes facilitate collaborative search. In the models of Gilbert et al., and those of Zirulia and Cowan et al., collaboration is modeled as a shift in the capabilities. In the Taylor & Morone models, collaboration concerns exchanging and jointly developing of skills. The NK landscape search models can be easily altered to model decentralized search. In case of a 2D opportunity or 2D the fractal landscape, collaboration would concern sharing of information on altitude, island or cell-state maps. So, most models facilitate an operationalization of collaborative innovation.
All of the landscape search models we have discussed have operational innovation heuristics that meet the Simonian capability restrictions. In general, this means that in the search process, there is no *a priori* idea how to improve technology, let alone how to efficiently engineer a 'good solution'. In Nelson & Winter model, this is modeled by a Gaussian performance displacement. In models with more elaborate operational search heuristics, this often boils down to not knowing the direction in which to search to improve the performance of the technology at hand. The NK and fractal landscape search, as well as the KENE search heuristics are the exceptions as the search in fact uses improvement feedback. In the opportunity landscapes of Fagiolo & Dosi and Silverberg & Verspagen, the strategic search heuristics steer the agent as if attracted by the performance of particular technologies and as such yield 'imitation' of technologies. So, in all models, agents have imperfect information and bounded rationality and are guided by signals and rules-of-thumb.

Lastly, let us assess the extent to which these landscapes facilitate introduction of an ordinal cost/ benefit structure. We in fact already discussed that in our evaluation of the landscape search models. As we can see in 3.3, some models already feature the performance of search of agents. As far as the

opportunity landscape models go, the Silverberg & Verspagen model already has a cost/ benefit model that would immediately indicate how successful an agent is. The Gilbert et al. model even has a comprehensive cost and benefit structure in place. Most of the other models do have variables which would allow introducing costs and also some kind of performance, e.g. the walk length and optimum fitness in the NK landscape, or performance versus travel and exploitation expenses in the Fagiolo & Dosi model. Note that the technology fitness can be immediately and conveniently linked to payoff through a market model similar to that in the Cattani & Winter model.
Please realize that we do not need this 'performance' to measure the effect of independent variables as is done in the fundamental studies described. Here, we use performance *indirectly* by using it in the selection device and thereby guide the emergence of behavior. Still, as we will see in chapter 6, we also develop highly simplified simulation models to discerning in laboratory settings the fundamental causes of particular behavioral patterns emerging.

From this overview, we see that our initial preference for the Kauffman NK landscape search model is convenient. The TCE factors can easily be defined operationally. The extent of technological interdependencies of elements, variable K, of the Kauffman landscape search model is suitable to immediately cover the intricacy dimension of technological complexity. Collaboration can be easily modeled as decentralized search in which complementarity by means of making agents confined to disjoint patches. Spillover can be modeled by 'leaking' (sub)strings of instances such that other agents can use them in own technology. As such, strings can be uniquely identified and they can hence be protected from being put to use. So, we then also have an operationalization of appropriability. The level of competition in the sector can be tuned by (as in the Cattani & Winter model) relating payoff to the fitness of the technology obtained, but hereby taking into account the performance of other agents. By doing this, we can also immediately hook the payoff in an evolutionary mechanism to implement an Alchian selection device.

		'Opportunity' landscapes			Fitness landscapes		
		Fagiolo & Dosi	Silverberg & Verspagen	Taylor & Morone	Kauffman, Lobo & Macready	Cattani & Winter	Gilbert et al.[1]
Technology	Codification	2D landscape location with different states [Capability]	2D landscape location with different states [Capability]	Subset of skills with different states [Instance]	Landscape string / Technology configuration [Capability]	2D landscape location [Capability]	Set of KENEs (capab. vectors) [Instance]
	Imposed structure	Proximities determine performance	Cumulation determines viability	Cumulation determines viability	Cumulative improvement of fitness	Cumulative improv. of fitness	Simonian cumul. improvement
Innovation	Operational heuristics	* 'Float' around * 'Sail' to island for imitation [Random]	Invest in site to discover techn. [Random]	Depth-first search for skills (* Exchange skills) [Structured]	* Local hill-climber / change configuration * Leap [Start random, then structured]	Move [Structured]	Alter KENE or draw new one [Random and structured]
	Strategical heuristics	Decision exploitation, exploration or imitate	* Radius & budget to invest in investig. site * Move	* Select innovation (* Solo/ Collaborate) (* Partner selection)	(Not applicable)	* Direction * Persistance in direction versus market feedback	* Increm./radic. (* Coll. strat.)
	Technological uncertainty	Random 'floating' Locations of unoccupied islands unknown, but agents attract imitators	Stochastic costs and unknown payoff of sites	Unknown skills structure but known innovations!	No foresight/ insight in epistatics. Unknown fitness of final optimum.	No foresight. Unknown fitness of final optimum.	No foresight. Unknown fitness final optimum.
	Capabilities/ properties	Location, skills (Together determine performance)	Location Capital stock	Firm size: # steps Skill set (location)	Location	Location	
	Cost/ payoff model	No. Firms have 'performance' though	Yes. Discovery costs vs payoff.	No.	No. Technologies have fitness though.	No. Firms have fitness though.	Yes. Innov. costs versus payoff.
Landscape features	Feature Parameter Eff. on search	Distrib. of islands (Not exposed) Productivity of techn.	Distr. costs & payoff (Not exposed) Activity	Structure of skill universe Distr. of # parents # steps required	Ruggedness Complexity K * Walk length * Fitness of optimum	Ruggedness Displacement drop h * Walk length. * Fitness of optimum	'Multi-peaked' (Not exposed) (Not clear)
	Feature Parameter Eff. on search				Scope. # components N * Walk length * Fitness of optimum	Tilt of landscape a, b * Fitness of optimum * Direction of search	

Table 3.3: Features of landscape search models

1. The reader is referred to the previous section. The low-level search model is strongly intertwined with the capabilities to collaborate.

Chapter 4

Methodology of simulation and simulation model building in social sciences

Before addressing the methodology of simulation model building, let us zoom out and comment shortly on simulation as instrument in the social scientist's toolkit. We are interested in why and how a social scientist would want to use simulation and what the objections to and limitations of using simulation in social sciences are. We will then provide a way to overcome part of the objections by introducing the reader to means to validate the simulation model.

Simulation is generally thought of as 'studying some phenomenon with a computer'. It is illustrative that ENIAC, the first ever mainframe, was developed during WWII primarily to calculate the ballistic trajectories of projectiles. As such, using a computer for computation or simulation by physicists, chemists and civil engineers is (almost without a doubt) valuable. The formal laws in engineering sciences that prescribe the behavior of the simulated entities lend themselves excellently for software implementation. A computer then particularly is there to overcome the overall complexity and computational burden, and to (cheaply) cast predictions.
Social phenomena typically occur under less clinical conditions and with fewer opportunities for empirical experimentation and validation. Practically, simulation in social sciences allows one, for instance, to rule out effects of incidents or environmental disturbances on empirical data or to overcome the scarcity of empirical data. In a process of validating theory, simulation allows to study cause-and-effect in a laboratory setting to infer on plausibility of theories and to overcome the ill-tractability of non-linear interaction of multiple entities. From this angle, Küppers and Lenhard (2005) argue we should see simulation in social sciences as a tool to gain 'insights about which interactions and structural presuppositions may be good candidates for explaining observed patterns of behavior' (Küppers and Lenhard, 2005). Axelrod (2003) takes this one step further and proclaims simulation actually complements inductive and deductive scientific reasoning as a valuable "third way of doing science". Axelrod argues simulation has both inductive as well as deductive qualities. On the one hand, simulation helps to get ideas of what might be causing particular patterns or anomalies in data. On the other hand, one might implement theories in some quantitative form and play with the simulation program to get ideas on the type of data that is to be expected if the theories are true.
Some authors however have voiced their concern about the use of simulation models in social sciences, as formal laws concerning the behavior of living subjects are much harder to establish. The criticism then does not particularly accrue to studies of behavior resulting from cognitively simple considerations (like studying the placement of fire escape routes in a building), but rather to studies of behavior resulting from cognitively complex considerations or behavior resulting from considerations in which factors that are hard to operationalize (like sentiments or preferences) play a substantial role. The classical argument against using simulation in social sciences is that it is easy to contrive different simulation models that produce the same (desired) output. As such, the output cannot lead to conclusions about the theory from which the simulation model is derived. After all, the field of Neo-Schumpeterian modeling started off with Nelson & Winter defying Solow's model by reproducing the same output using the same input however using a completely different model!

So, the biggest concern with simulation in social sciences actually is the internal as well as external

validity. Luckily, there are ample instruments to bolster validity of a simulation model[1] and thereby meaningfully relate what is being simulated to what is being conceptually investigated.
Let us first see what there is to do to come to a simulation model and then where we have to be aware of validity issues and how we can bolster validity. In putting simulation to use as a research instrument in experimental research, the researcher needs to provide:

1. A description of a complex phenomenon in the real, empirical world
2. A (theoretic) framework of causal relationships as a conceptual abstraction of the empirical phenomenon
3. An operational model of the framework established by formulating heuristics, operational representations of actual processes and functions
4. A computer implementation of the operational model (i.e. the simulation model) requiring additional assumptions to overcome limitations rising
5. Values for the operational parameters to represent the actual system and to put the framework to the test
6. Statistical analysis of generated data and robustness study of findings

During translating of a model to a more specific and operational level, the researcher needs to assure the validity of the model produced and eventually the validity of the final simulation model with the real-world phenomenon studied. In order to interconnect to ordinary research methodology with simulation model design methodology, we will depart slightly from the terminology of Sargent (1998)[2] and relabel the description of the real-world phenomenon as Sargent's 'problem entity' and associate the Sargent 'conceptual model' with the theoretic conceptual framework (and not the operational definition thereof). This will allow us to squeeze in a distinction in the operational definition and the software implementation of the operationalization. At a first glance, this distinction appears to be superfluous, but some authors actually distinguish separate dimensions approving it. This distinction is there both for the sake of the argument as well as to be able to attribute issues at play in simulation to what Küppers and Lenhard (2005) call 'partial autonomy' of the simulation model. As long as there are errors related to the actual programmatic implementation and intrinsic issues related to the use of computers (e.g. no need to solve systems of equations, working around discretization, truncation issues or (in appreciation of the history of computerized calculation) having to apply 'Arakawa tricks'), we prefer being able to pinpoint the exact cause.

The researcher needs to safeguard adequacy of the models at the various levels. To get an impression of what is involved, we will connect the validity concepts of Carley (1996) to the adjusted Sargent terminology. We then have a validity concept for each translation downward. We perceive conceptual validity as the adequacy of the theoretic framework in characterizing the real world. Operational validity is the adequacy of the operational model in representing the theoretic framework. Implementation validity concerns the correctness and adequacy of the program-technical implementation of the operational model. Papers on the methodology of simulation in social sciences underexpose the value of selecting the 'appropriate' values for parameters and we will introduce that here, too. Hence, simulation or internal validity is perceived as the adequacy of the *quantified* simulation model and the parameter-settings in representing the conceptual framework and reflecting the behavior addressed in it. Poor internal validity usually indicates program-technical flaws, relates to poor design choices and detrimental design assumptions. Finally, we have external validity that concerns the adequacy and accuracy of the computational model in representing the real-world phenomenon.

In *explorative* simulation research, scientists start developing an operational model to create and

1. Henceforth we will omit the specification 'in social science'. The reader can safely assume we mean a 'simulation model in social science' if we write 'simulation model'
2. To keep this chapter concise we will omit a thorough description of this terminology but rather introduce it ad-hoc in the next paragraphs as we feel that suffices. We refer the reader to Sargent's writings for detailed information.

refine theories bottom-up, at least to some extent. Here, we rather conduct *experimental* simulation research, and derive our operational model from an existing theory[3].
We will now discuss the various aspects involved in designing, operationalizing, implementing and quantifying the model to either explore or test a conceptual framework. We will hereby follow the validity concepts just defined.

4.1 Internal validity

As far as internal validity goes, experimental research geared toward testing specific theories finds itself in a catch-22 situation. On the one hand, the internal validity of the simulation model is assessed by showing that the model is capable of confirming causal relationships in the conceptual framework (say, 'claims'), while, on the other hand, we need to test the main hypothesis (which is the ultimate causal relationship) and thus implicitly need to presume the model is valid already.
This leads to the following odd situation. If we fail to confirm the hypothesis (or other causal chains in the operational framework), we can only conclude that the internal validity is poor. If we however succeed in confirming the hypothesis and the other causal chains, we kill two birds with a single stone: both the model is internally valid *and* we meet the operational objective of the research.

Failing to confirm the hypothesis or significance of causal relationships can have several causes. ~~At a low level, it can be caused by invalid values of some parameters or due to errors in the~~ assumption-rich quantified operationalization. One would first readjust values in an ongoing exploration of the parameter landscape and only after thorough exploration (which can only rarely be exhaustive) subject the actual implementation to a bug chase. Only after rigorous white-box tracing and boundary condition and degeneracy testing (i.e. studying behavior of the model in isolation), we should contest the internal validity of the operational model and thus return to the drawing board to redesign the operational model. Although it certainly is not unusual to search for flaws in the model at higher levels, the researcher should at least practice parsimony in doing so. Raising questions about the validity of the theoretic framework presumably at best yields scorn of the scientific community.

It is very well likely that the researcher has to go through several iterations of stepwise formulating and translating the conceptual model into an operational model and then into the simulation model before succeeding in confirming the main hypothesis. The researcher will be running test simulations and checking the results, searching for bugs and fixing them, returning to the drawing board to redesign the operational model if required or even adjusting the scope of the conceptual model. During early passes, the operational model is shaped and quantifications searched. During later passes, there is more confidence in operational and implementation validity, the researcher focuses on experimenting with parameter settings and only occasionally has to move upward in contesting earlier translations.
In order to facilitate contesting the internal validity, it is advised to derive more claims from the conceptual framework. The more of such 'circumstantial indicators', the easier it gets to test the simulation program and indirectly the operational model. It is also possible to derive properties of the various operational simulation model components. The researcher can then use these properties in degeneracy and extreme condition testing to assess proper functioning of the simulation model components. We then have conceptual circumstantial indicators and software component properties to prop circumstantial internal validity.

Apart from formulation of the simulation model, internal validity also relates to the 'reliability' of the output data. The model should be able to yield the same tendencies in the data for different

3. Note that Axelrod his 'third way of doing science due to the combination of deductive and inductive qualities' appears to relate to the fact that we can indeed do both explorative and experimental research with the same code base.

random seeds. A lack of consistency (internal stochastic variability in terms of Sargent (1998) and absence of or premature convergence in terms of Alkemade et al. (2006)) is an indication internal validity is insufficient. Checks of consistency often simply take the form of robustness checks.

4.2 Translating the theoretic framework into an operational model

While the descriptive accuracy of the model increases with every variable or parameter added, it becomes increasingly difficult to interpret the outcome of simulation runs and to disentangle the actual causal chain. So, there is a trade-off between explanatory power and descriptive accuracy, and indeed the modeler has to balance between keeping it descriptive (KIDS) and keeping it simple (KISS) (Pyka and Fagiolo, 2005). There is yet another danger in making a model descriptive: the researcher might over-fit the operational model by adding too many parameters. This might allow 'calibrating' the quantified simulation model to reproduce claims on causal relationships in the conceptual model and the hypotheses even when operational validity is poor.

Operational validity is supported by justifying the selection of operational core models that have been used and assumptions allowing operationalization. Here, we need support for our choice of the NK landscape search as representation of R&D, for instance. Rather than starting from scratch and designing a model by conjecture, a model should be based on realistic (and empirically robust) assumptions (ROAS) (Frenken, 2005; Pyka and Fagiolo, 2005) and using a model that has already been around for a while and withstood the test of time and scientific debat. This last method is referred to with the acronym TAPAS, which stands for "take a previous model and add something" (See Frenken, 2005). Frenken (2004) suggests a couple of such 'core models'. We will simply sum them without going into detail: Game Theory to model strategic interaction, replicator dynamics to model competition and industrial dynamics, polya urn models to model diffusion, graph/network theory to model the functioning and dynamics of networks and finally the NK landscape to model problem-solving in complex systems.

Usually, scientists limit the theoretic framework to only a few (abstract) factors, so intricate modeling issues occur as of the definition of the operational model. Hereby we have to seek a balance between descriptiveness and simplicity. We however have to operationalize (all) factors in the framework in any case. In doing so, we have to specify parts of the concepts in the framework. Apart from the factors that will be used as operational definitions, we often have to introduce 'auxiliary' parameters to conceptually complement these factors in order to establish external validity. For instance, modeling R&D as NK landscape search with innovation costs implies we will have to specify how an agent obtains a starting point and at which costs. We will also have to set such auxiliary parameters and justify for the value(s) chosen.

Apart from the normal conceptual and auxiliary parameters, there is a specific set of 'technical' parameters (See Alkemade et al., 2006). These parameters closely relate to the assumptions underlying the exact (quantified and programmatic) implementation of the simulation and have no empirical or theoretical counterpart. A simple and crude example is fixing the number of agents in the population for it is easy to work with fixed length arrays. Another, less obvious example is that some authors for example 'optimize' agent heuristics by applying genetic programming techniques (See e.g. Alkemade, 2004; Tesfatsion, 1998) hereby having to specify the number of generations, the mutation variation and elite fraction. The latter 'technical' parameters of course have no conceptual counterpart.

Obviously, the number of such parameters should be kept at a minimum, but sometimes are unavoidable. To single out effects of those technical parameters, it is crucial to be sure to take a reasonable value prior to starting simulations and afterward investigate the robustness of the conceptually meaningful conclusions for changes in the value of these technical parameters.

In case of experimental simulation modeling, the formulated operational model should allow translating the hypotheses from the conceptual to the operational level and thus eventually allow statistical tests.

4.3 Implementation

Sargent advises researchers to choose a language or development environment specific for simulation (e.g. RePast, Swarm, Quicksilver, Ascape) if available and suitable (with regard to flexibility) rather than starting from scratch using a general-purpose language (e.g. C/C++, Java, Pascal).
Due to the non-linearity and stochasticity in behavior (and thus measured values of the dependent variables) it is difficult to discern the causes of poor internal validity: are there bugs left in the code or are there flaws in the operational design? No researcher wants to go back having to verify the implementation once started thorough simulations. It is therefore advised to test submodules thoroughly (input-output) and trace through code execution. In doing so, extensive logging and 'operational graphics' are no luxury either. As one can apply ordinary test procedures, the researcher can consult arbitrary manuals on Quality Assurance and software testing.
As a professional software engineer working at a software company with an extensive code-base containing much legacy code, I know that quick hacks in obscure portions often cause problems. This should be taken as a hint that one should be careful when revising the code-base in later validation iterations.

4.4 Selecting parameter values

As most theories are qualitative in nature in social sciences, a translation into a simulation model of quantitative nature will definitely be a challenge for the researcher. The actual parameter values need not be proportional to the (approximations of) empirical values. Despite the power of computers, the researcher will have to limit him/herself to exploring only part of the parameter universe.

In literature, it is suggested that the researcher can best calibrate the parameters by using empirical data (See e.g. Werker and Brenner, 2004; Carley, 1996). If the researcher is not interested in using particular histories for reenacting but rather uses simulation to generate ideas, the requirements can be reduced to being able to reproduce 'conceptual claims' or 'stories' about the real world.
As mentioned before, the researcher finds itself in a catch-22 situation: testing the main hypothesis requires a(n) (internally) valid model, but the model is (internally) valid only if it is able to confirm the causal relationships in the conceptual model. The researcher thus needs to find a set of parameters that both confirms the hypothesis and thereby (indirectly) provides evidence of the internal validity. As mentioned before, circumstantial validity indicators should provide confidence to start the sometimes lengthy search for correct parameters.

Let us now compile a recipe (ad hoc) to bootstrap ourselves out of the catch-22 situation by incrementally picking (multiple) suitable values parameter-by-parameter for further investigation of other parameters. The researcher will nonetheless need to start with some 'intuitive' or 'reasonable' values to create a starting point. A set of values is 'reasonable' if simulation outcomes look OK, i.e. if there is 'face validity'.
One will typically start with selecting a central parameter strongly affecting model behavior and investigate the three-dimensional space of this parameter and the independent and dependent operational variable. If a parameter does sort a *simple* effect on the measured dependent variable, it usually is high on the one side and low on the other side of the continuum. One should then select a suitable range and granularity and pick a few values (at least one in both interesting regions) for further inspection. If the effect is more erratic or there is no effect at all, there might

be other variable(s) intervening. If the conceptual interpretation of the erratics is not too much of an eyebrow raiser, we should be inspecting this parameter later and otherwise inspect technical parameters and programmatic implementation. Such erratics does often lead to adjustment of values of operationally adjacent parameters.
One subsequently selects another parameter with a (relatively) strong effect on model behavior and repeats the procedure for all scenarios spanned by the values for the previously investigated parameters. So, we gradually expand the number of parameters involved in the simulation and per new parameter scan all possible combinations of settings already selected for the parameters already picked. It is possible there are several passes required for particular parameters.
Not only operational variables with a conceptual counterpart need to be involved, but also the so-called auxiliary parameters.
Selecting reasonable values for the 'technical' parameters is particularly important, as the first few steps will primarily concern 'calibrating' the model to claims on causal relationships or ideas of the actual outcome.

4.5 Actual simulation and data analysis

Once the researcher has one or multiple starting scenarios (i.e. parameter-value sets), (s)he can start investigating the model behavior in more detail. Hereby, one has to set the range and granularity of the parameters and independent and intermediary variables by performing a quick scan of the range and a more fine-grained inspection of interesting ranges.

Obviously, the researcher should focus on measuring the effect of the independent and mediating variables on the dependent variable. We will not go into the exact basic statistic analysis for laboratory data, but one can apply ordinary regression techniques, for instance, as there is a clear idea of the underlying (non-linear) model (after all, we have a conceptual model). Hereby, the researcher should also inspect the effect of the auxiliary and technical parameters. *Ideally*, the conceptual model captures most of the behavior of the system, but it might be so that particular auxiliary parameters have a greater effect than a mere proportional shift in outcomes. These parameters -which are thus conceptually unaccounted for- should be isolated and certainly involved in robustness analysis.

In Alkemade et al. (2006) is noted that technical parameters need to be treated separately from the model parameters. As technical parameters can easily break validity, the researcher should investigate the robustness of a(n) (internally and externally valid) simulation model for variations in the technical parameters. It often is absent because of limited resources and time and because researchers are not aware of the consequences such technical parameters can have on the simulation results.
As a note on the side, we claim that a thorough treatise would also involve investigating the robustness for changes in the assumptions underlying the operational model. Somewhat philosophical, but in practice this often is done (implicitly) in follow-up studies or in studies of fellow-scientists in which (slight) variations of the model at hand are investigated.

As hinted in the subsection on internal validity, internal *variability* in output metrics should be measured by rerunning the scenarios for different random seed values. If the variability is too high, the internal validity is relatively poor, as particular relationships might be (in)significant by accident.

4.6 External validity

Where assessment of internal validity is based on reproducing the hypothesis and 'claims' on the causal relationships in the conceptual model, assessment of external validity is based on reproducing 'stories' and 'events' (See Sargent, 1998, on event validity) and 'stylized facts' (See Frenken, 2005; Pyka and Fagiolo, 2005, on the ROSF method). Another, more stringent option is to validate the model outcome by using historical data. If one attunes the model parameters to reproduce such a historical strand, one obviously calibrates the model parameters to empirical data.

If such data, stylized facts or stories are not available, one needs to resort to less specific methods. Sargent suggests a method called 'face validity'. The researcher hereby asks a panel (of experts in the field) to have a look at and comment on the (graphical) simulation output. If the output does not look reasonable to the panel, the model is classified as externally invalid.
It is noted that face validity is often already implicitly used during testing and quantifying the operational model; if the model produces ridiculous output, you know there are bugs or flaws in the model. Face validity hence also is an indication of internal validity.

If confrontation with empirical knowledge is impossible, one might resort to (statistical) cross-validation with other models at a quantified level. However, as far as Neo-Schumpeterian models goes, most of these models have unique features making them ill-suited to use them for comparison. As one however often relies on one or more core models (i.e. those mentioned in the subsection on translation to operational models) already in use, the (implementations of) core models can be cross-validated by fine testing the (quantified) submodules in the implementation. Here, the NK landscape core model is well-studied and has well-understood characteristics, allowing external validation of the search metrics in isolation.

Chapter 5

Neo-Schumpeterian model of R&D collaboration

In this chapter, we devise an operational model to study the properties of R&D collaboration under different technological complexity levels. The operational model in fact is an operational Neo-Schumpeterian framework in which we fit several operational model components that allows us to operationalize the factors in the adorned TCE theory. The idea is to implement this operational model as a simulation model in which we can set the parameters of the operationalizations of the TCE factors on the input side, run simulations in which an evolutionary mechanism weeds out inferior R&D strategies and to eventually measure the emerging collaboration propensity. We can then systematically vary the factor parameters and analyze the effect on collaboration regularities that emerge. This will allow verification of operationalizations of the theoretic causal relationships.

In the following section, we will provide an overview of the operational model. We will hereby pinpoint the operational Neo-Schumpeterian framework, the major model components as well as the operationalization of the TCE factors based on those components. We will indicate in which sections ~~the specifications of the various components can be found.~~ In ~~subsequent sections, we will describe~~ the various model components. We will thereby not only pay attention to the operational definition, but also to the economic interpretation of the operationalizations and possible shortcomings of those operationalizations with respect to the context-free definitions provided in section1.3, basic intuition and the economic theories present in chapter 2. In the last section, we will reformulate the basic TCE model relationships formulated in subsection 2.3.2 into operational hypotheses which we will test using the simulation model. We will not discuss the actual implementation into software.

5.1 Outline

In this section, we will provide the outline of the simulation model, sketch the relationship of the various simulation components with the TCE conceptual model and the Neo-Schumpeterian framework. The outline consists of hinting on the various components required, their link to each other and in which sections in this chapter the more detailed specification can be found.
By now, we have an understanding of the fact that a Neo-Schumpeterian framework starts out with a representation of an industry in which there is evolutionary conditioning of strategies of agents by having entry, exit and imitation of these strategies. Exit and imitation strongly depends on the performance of innovation as technology provides financial means to cover expenses. The activities for innovation in turn depend on the strategy pursued by the agents.
One of the most difficult tasks Neo-Schumpeterian economists face is how to model innovation. As mentioned before, the general approach is to have agents search a technology landscape to come up with innovations. Often the choice for the landscape is closely related to the subject matter of the research. Here, we will opt for a technology landscape model suggested in subsection 3.2.4 that allows us to operationalize the factors in the TCE model. We also require a reflection of the industry in which these agents operate, so as to meet the Neo-Schumpeterian framework.
As hinted, we have to fit our conception of the industry in which the agents operate into this Neo-Schumpeterian framework. This conception facilitates operationalization of the TCE factors and of course meets the Neo-Schumpeterian premises.

We will first look at the backbone of our operational model, the Neo-Schumpeterian framework. In a nutshell, the operational model enables us to run a simulation for R consecutive periods in which agents conduct R&D projects. Agents hereby follow their R&D strategy thereby incurring certain costs that they try to recover by bringing the technology they discover to the market to earn payoff.

If an agent has an R&D strategy that structurally yields inferior technologies, the returns on R&D are (too) low and the agent in question is likely to go bankrupt and exit the population, while if the R&D strategy produces superior technologies, entering agents are likely to imitate and thereby propagate the superior strategy. We thus see that 'superior' strategies survive at the expense of 'inferior' strategies.
The Neo-Schumpeterian device of selection is the market. All agents share this market and hence are direct competitors. The market has a limited capacity of M technologies and L technologies per agent. At the beginning of the next period, the market disburses exactly D credits, which are distributed over the agents according to the fitness of technologies they sell. This market model is further specified in section 5.4.
The initial population consists of A agents, but over time, the population composition is changing as agents can exit and enter. As each agent i starts with capital stock Q^0 and pays a fixed amount C per period, the capital stock Q_i might drop below zero if this agent is unable to get sufficient payoff. The agent is then put out of business. Upon bankruptcy, the agent is eliminated from the population, its technologies and patents are removed from the market. Exit is described in more detail in section 5.6.
On the other hand, depending on the concentration of the market, agents enter. If the concentration increases, the probability of entries increases, which reflects that, in reality, firms believe they will be able to get a piece of the pie if there are only a few firms. The mechanism to decide whether an agent will enter and -if so- which agent it will imitate will be described in detail in section 5.5.

Let us now look at the specific industry conception that allows us to study the research question and how the factors in our TCE model are operationalized. Each period, each agent invents a new technology or reverse engineers with probability ρ a technology already on the market which is used to start an R&D project. An agent can only be involved in one R&D project. This R&D project is operationalized as search on a technology landscape. The agent(s) involved will follow a hill-climber algorithm on an NK technology landscape to improve the fitness of the technology until the local optimum is reached. This R&D project will be finished that same period. The agent(s) will then bring the locally optimal technology to the market. By collaborating, agents share capabilities and hence are likely to find more fit technologies, but agents also have to share the payoff and license fees. We will describe collaborative innovation in more detail in section 5.2. An agent will incur no costs for invention, reverse engineering or innovation, only a fixed number of credits C which is the same for all agents. We will explain the choice for these limitations in section 5.2.
As far as our TCE model goes, the factor *complexity* is operationalized as the parameter K which tunes the ruggedness of the landscape. The operationalization of the factor *complementarity* relates to the patch of control of agents and the fact that agents can join capabilities in search to find more fit technologies. The operational definition of this 'search' (both solo as well as collaborative) can be found in section 5.2 on the technology landscape search model.
There is no obstacle for agents to bring (nearly) the same technology to the market which can actually happen by reverse engineering or spillover. According to the TCE framework, the collaboration propensity of firms depends on the factor *appropriability*. In the operational model, we allow agents to appropriate the returns of R&D by having them 'patent' their technologies and receive a license fee of each agent that sells technology infringing the 'patent'. As this 'patenting' is a part of the payoff calculation scheme, it will also be described in section 5.4. The factor *level of competition* can be introduced e.g. by decreasing the overall payoff, by tuning the preference for quality or having a high entry intensity. Agents following inferior strategies will then be forced into demise more quickly. We will discuss competition in section 5.4 in more detail.
By effect of the discussed evolutionary framework, collaboration propensity is emerging. Agents use a threshold δ to determine the R&D project configuration: i.e. whether or not to collaborate, and if so with whom. We in fact have devised a matching algorithm that is further specified in 5.3.

Agents with a poorly performing strategy δ are forced to exit, while entrants (so, not the initial agents) imitate the strategy δ of agents with superior capital stock. So, collaboration propensity as output of this strategy δ indeed emerges. This concept of entry and imitation will be described in section 5.5.

We will be using the framework to conduct experimental research. In order to answer the research questions of this thesis, the collaboration propensity measure is calculated for each simulation run. By systematically varying the parameters for the TCE factors and running each scenario for a number of seeds, we get an impression of the phenomena and the relationships at hand. In section 5.7, we will formulate particular measures to express the propensity to collaborate and then relate those measures to input variables to address the hypotheses as formulated in 2.3.2.

5.2 R&D as technology landscape search

R&D activities and their inherently uncertain outcome are modeled by technology landscape search. In section 3.2, we provided a framework to specify such a technology landscape search model. Recall that we have to describe the (operational) conception of technology (most commonly either an 'instance' or implicitly as outcome of 'capabilities'), the (operational) conception of the innovation process (most commonly an 'explorative discovery' of a landscape or 'improving by learning' respectively) and the experimentation landscape features (e.g. ruggedness of the landscape or uncertainty of improvement). Here, we will concurrently expand the solo landscape search concept to a collaborative landscape search to model R&D collaboration. We endow agents with different fields of expertise to which their innovation activities are confined. They, as such, search different sections of the landscape in an effort to improve the whole technology they develop in co-operation. We will also specify the three dimensions of a technology landscape for the NK landscape we have chosen here, and immediately define the operationalization of the factors *complexity* and *complementarity* in the TCE model.
After discussing the three dimensions in the technology landscape search framework, we will confront the thus obtained operational core model with the definitions provided in section 1.3, the presumptions of the Neo-Schumpeterian framework, the conception of the TCE factors and some additional insights on innovation.

5.2.1 Operationalization of technology

We have chosen for an 'instance' technology landscape (as opposed to a 'capabilities' landscape). We hence have to come up with a codification of the technologies that make up the technology landscape and an interpretation for the codification. Here, technology is conceived as a 'comprehensive specification' (see 1.3) of the activities and choices in between (but excluding) R&D activity and market performance. To prevent becoming too esoteric, we conceive technology still primarily as a specification of the process techniques to use and specifications of some product. In line with the NK landscape model which we have adopted, we will encode this technology as a so-called Boolean string T in $\mathbb{B}^N$.
The NK landscape model of course is particularly known for the exogenous, high-end imposed relationships between the various technology elements (see 3.2.2). Each element affects the fitness of K other elements. This fitness is perceived as the technological performance and takes values between '1' (functioning perfectly) and '0' (dysfunctional). For an introduction to the use of the traditional NK landscape model, the reader is referred to section 3.2.2.

The fitness of the whole technology simply is the arithmetic mean of the fitness values of the individual elements (which however are affected by the choice for on average K other elements).

The common definition for the fitness $F : \mathbb{B}^N \rightarrow [0, 1]$ of a technology T is defined as:

$$F(T) = \frac{1}{N} \sum_{i=1,\ldots,N} F_i(T[i]|T[1], \ldots, T[i-1], T[i+1], \ldots, T[N]) \tag{5.1}$$

We see that the contribution of an element i to the fitness of the technology $F(T)$ is $F_i(T[i])$ but that this depends on the values of the other elements as well. On average, only K of the $N-1$ of the conditional arguments matter. Whenever the state of a single element is changed, not only does the fitness of that single element change, so does the fitness of all K dependent elements. This change in fitness has no correlation with previously attained fitness (See Altenberg, 1996). By varying the landscape complexity K, the number of component interdependencies (or epistasic relationships) are tuned. In the current implementation, the interdependencies of an element i are established by drawing K distinct elements from $\{1, \ldots, i-1, i+1, \ldots, N\}$ at *random.*
A highly modular landscape is one with nearly independently functioning elements allowing the researcher to engineer new combinations with high fitness by simply joining elements with high individual fitness values. Technological components have clearly defined interfaces and can be combined without deteriorating the fitness of one another. A highly complex landscape is one consisting of strongly interdependent elements forcing the engineer to review many combinations of elements and constantly monitoring the effect of changes in single elements on other elements and the total fitness as there are many 'incompatible' combinations with low fitness. Components are hardly distinguishable or have unspecified interfaces. Simply joining components, even if relatively fit, is likely to lead to poorly functioning technology. If complexity K is high, the landscape is said to be 'rugged' as the fitness has many peaks and valleys.

We see that this technology fitness value is an aggregate measure of overall fitness value, of all individual elements. In reality, agents will not (necessarily) be able to assess the fitness of individual elements, but rather only those belonging to its field of expertise. In line with the patch concept as defined in Kauffman and Macready (1995) and Frenken and Valente (2003), we introduce such a field of expertise $E \subseteq \{1, \ldots, N\}$. A 'patch' simply is a set of consecutive indices to technology elements. A field of expertise E of size S is established by drawing an offset in $\{1, \ldots, N\}$ at random and assigning the subsequent S indices to the set E wrapping around at N. The concept of patch or Simonian fitness is defined as:

$$F(T, E) = \frac{1}{|E|} \sum_{i \in E} F_i(T[i]|T[1], \ldots, T[i-1], T[i+1], \ldots, T[N]) \tag{5.2}$$

We can now talk of a subjective assessment of fitness $F(T, E)$ which depends on the expertise E of an agent assessing the technology. We hereby meet the Simonian concept of bounded rationality and imperfect information. As we will see in the next subsection, we introduce decentralized search as in Frenken and Valente (2003) and thereby operationalize the TCE concept of complementarity as well.

This Simonian fitness $F(T, E)$ has interesting properties. Note that if $|E| < N$, the fitness $F(T, E)$ of a random technology T is an average of the fitness of fewer elements and hence has a larger coefficient of variation (but the same mean 1/2). So, if the field of expertise E is severely limited, the agent does a poor appraisal of the actual fitness of the technology; the 'estimated' fitness can be way too low or way too high. The larger $|E|$, the closer $F(T, E)$ is to $F(T)$, in probability.

With this encoding of technology as a binary string and an assessment of the fitness of this technology, it is easy to contrive a heuristic to improve the technology by trial-and-error. We will introduce the reader to such a search heuristic in the next subsection.

5.2.2 Operationalization of innovation

The search on a technology landscape is a metaphor for innovation. Innovation is conceived as an ongoing process of trying to develop technologies with better performance. At an operational level, this takes the form of improving a technology obtained by invention or by reverse engineering by means of trial-and-error search (to meet Simonian bounded rationality). An agent experiments with singular changes (and hence is called 'local search') to the technology and accepts the fittest one thus obtained. The agent repeats this procedure until no change brings about an increase in fitness. As such, the agent follows, what is called, a 'hill-climbing' or 'adaptive walk' heuristic. We will now formalize this procedure and later expand it for collaboration of two agents.

Innovation as landscape search

In line with Simonian behavioral assumptions, we confine agents to their field of expertise. Agent i only explores the set $E_i \subseteq \{1, 2, \ldots, N\}$ of dimensions of the landscape, where $e \in E_i$ refers to component e of T (with state $T[e]$). We model innovation as 'adaptive walk', a local search starting at a focal technology, testing all $|E_i|$ possible local 'mutations' and selecting the best as new 'focal' technology. An innovation is said to be locally optimal if the current focal technology can no longer be improved. Let us formalize this.

The flip function $X : \mathbb{B}^N \times [0, N] \to \mathbb{B}^N$ is defined as:

$$X(T, f) := \begin{cases} |1 - T[i]| & i = f \\ T[i] & i = 1, \ldots, f-1, f+1, \ldots, N \end{cases} \tag{5.3}$$

Technology $\hat{T} = X(T, f)$ hence is equal to technology T apart from the fact that element f has been 'flipped'. The set of local, singular mutations $M(T, E)$ of T given expertise set $E \subseteq \{1, \ldots, N\}$ is then defined as:

$$M(T, E) := \{\, X(T, e) \mid e \in E \,\} \tag{5.4}$$

Now, a single hill-climber step with expertise E and fitness evaluation set E' is defined as:

$$T_m^f = \arg\max\{\, F(T, E') \mid T \in M(T_{m-1}^f, E)\} \tag{5.5}$$

We see that this hill-climber step hence moves from focal technology T_{m-1}^f to the (new) focal technology T_m^f, hereby this T_m^f is the fittest technology in the set of all local mutations of T_{m-1}^f with respect to the field of E, $M(T_{m-1}^f, E)$.

We can now formulate the actual hill-climbing algorithm. This algorithm starts from an arbitrary focal technology T_{i0}^f and goes through consecutive focal technologies $T_{i0}^f, T_{i1}^f, \ldots$ following the hill-climber step with expertise E_i as described above. As soon as $T_{iL}^f \in \{T_{i(L-1)}^f, \ldots, T_{i1}^f, T_{i0}^f\}$ either a loop is encountered (which is 'locally' optimal) or the local optimum has been found. If the local optimum or a loop is encountered, the algorithm stops. Note that T_{m-2}^f is in $M(T_{m-1}^f, E)$ such that stopping of the algorithm is assured.

We now have the outlines of what constitutes an R&D project in our operational model. An agent will invent a technology (modeled by picking a random landscape string) or reverse engineer one of the technologies already on the market. Taking this starting technology, an R&D project is started and by hill-climbing the agent will reach the local optimum. The agent brings this locally optimal technology to the market.

The agents now also suffer from several Simonian behavioral restrictions. Agents have limited innovation capabilities as they can only perform trial-and-error. Agents have limited innovation freedom as their field of expertise is limited $|E| < N$. Agents furthermore rely on $F(T, E')$ with $|E'| < N$ rather than on $F(T)$ during hill-climbing, as such we introduce 'imperfect information' of the agent of the actual fitness.

T	F	F_1	F_2	f_1	f_2	f_3	f_4
0000	0.41	0.46	0.36	0.59	0.33	0.70	0.02
1000	0.35	0.23	0.48	0.13	0.33	0.70	0.25
0100	0.24	0.36	0.12	0.59	0.13	0.22	0.02
1100	0.18	0.13	0.24	0.13	0.13	0.22	0.25
0010	0.48	0.57	0.40	0.81	0.33	0.77	0.02
1010	0.44	0.36	0.51	0.39	0.33	0.77	0.25
0110	0.37	0.47	0.27	0.81	0.13	0.51	0.02
1110	0.32	0.26	0.38	0.39	0.13	0.51	0.25
0001	0.49	0.52	0.45	0.59	0.46	0.70	0.20
1001	0.48	0.29	0.68	0.13	0.46	0.70	0.65
0101	0.48	0.74	0.21	0.59	0.90	0.22	0.20
1101	0.47	0.51	0.43	0.13	0.90	0.22	0.65
0011	0.56	0.63	0.49	0.81	0.46	0.77	0.20
1011	0.57	0.42	0.71	0.39	0.46	0.77	0.65
0111	0.60	0.85	0.36	0.81	0.90	0.51	0.20
1111	0.61	0.64	0.58	0.39	0.90	0.51	0.65

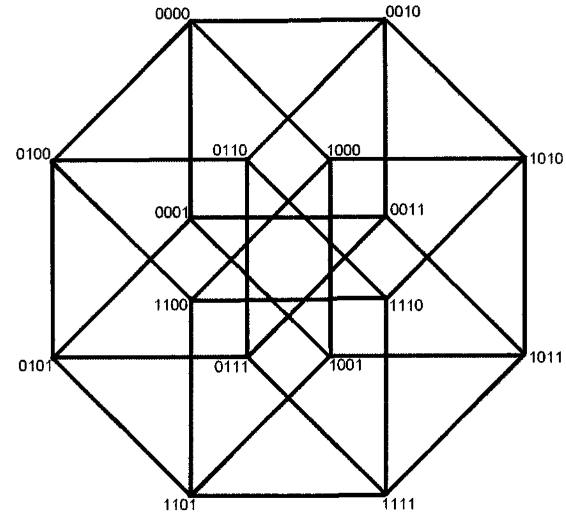


Table 5.1: Fitness values for the 16 technologies for an example landscape with $N = 4$, $K = 1$ and $E_1 = \{1, 2\}, E_2 = \{3, 4\}$.

Collaborative landscape search

Central to this essay is that collaboration allows agents to partially overcome these limitations. R&D *collaboration* is modeled by expanding the search algorithm to have two agents i and j search together. If agent i conducts R&D alone, $E' = E = E_i$, while now $E' = E_i \cup E_j$ and $E = E_i$ ($E = E_j$) if i (j) executes its R&D steps.

Both agents start from the same focal technology and construct a set of mutations according to their respective expertises. As soon as the agents have both reached their new focal technology, both agents start from the best of those two new focal technologies, i.e. a single hill-climber step in a *collaborative* project is simply defined as:

$$T_m^{fc} = \arg\max\{F(T, E_i \cup E_j) | T = T_{im}^f, T_{jm}^f\} \tag{5.6}$$

The collaborative R&D project is finished as soon as none of the agents can improve the current focal technology or a loop occurs.

Examples

Let us have a look at three examples of search on a landscape starting at the same point, to then compare the steps in the trajectories and the final search outcomes. In the first two cases, we have two agents with different fields of expertise conduct a landscape search and, in the last case, we have these two agents collaboratively conduct a landscape search. We have provided the landscape given in table 5.1, hereby $F_i(T)$ is a shorthand notation for the Simonian fitness $F(T, E_i)$ and f_j is the fitness of a single element j (of course affected by the setting of the elements through the technological interdependencies). In this example, we let an agent 1 with expertise $E_1 = \{1, 2\}$ search, starting from technology 0100. According to the Simonian fitness assessment of agent 1, the fitness of 0100 is $F_1 = 0.36$. Agent 1 will inspect technologies 1100 ($F_1 = 0.13$) and 0000 ($F_1 = 0.46$). Agent 1 will then select technology 0000 as new focal technology to see whether he can even further improve this technology. Agent 1 will thus inspect 1000 ($F_1 = 0.23$) and 0100 ($F_1 = 0.36$). As there is no further improvement possible, agent 1 has found the Simonian local optimum. Technology 0000 has global fitness 0.41, which is far from the global optimal fitness of 0.61 of technology 1111. Due to the agent his Simonian capability limitations, the agent cannot alter elements 3 and 4 and hence in the first step not escape to 0110 ($F_1 = 0.47$) or 0101 ($F_1 = 0.74$). If the agent would in addition not suffer the limited fitness assessment and be guided by F rather than by F_1, the agent

would pick 0101 ($F = 0.48$).
In the second example, we let agent 2 with expertise $E_2 = \{3, 4\}$ search, also starting from technology 0100. According to the Simonian fitness assessment of agent 2, the fitness of 0100 is $F_2 = 0.12$. Agent 2 will inspect 0110 ($F_2 = 0.27$) and 0101 ($F_2 = 0.21$) and select 0110 as new focal technology. He will then inspect 0100 ($F_2 = 0.12$) and 0111 ($F_2 = 0.36$) and we see that agent 2 can even further improve the technology and hence selects 0111 as new focal technology. Agent 2 will however discover that it will find no improvements amongst the next two mutations 0101 ($F_2 = 0.21$) and 0110 ($F_2 = 0.27$). The Simonian fitness of the Simonian local optimum reached by agent 2 hence is 0.36, while the global fitness of technology 0111 is $F = 0.60$.
We see that both agent 1 and agent 2 have not obtained the Simonian global optimum, which would be 0111 for agent 1 with $F_1 = 0.85$ and 1011 for agent 2 with $F_2 = 0.71$. We also see that it is very likely that the limited capabilities and/ or the limited fitness assessment restrict the agent in reaching globally top-fit technology or even the global optimum.
In the last example, we let agent 1 and 2 collaboratively conduct R&D. Their joint expertise $E_1 \bigcup E_2$ equals the whole search space, so we can simply use F when selecting a focal technology. Both agents start from 0100 with global fitness $F = 0.24$ which is perceived by both. Agent 1 now investigates the mutations 1100 ($F = 0.18$) and 0000 ($F = 0.41$) and hence propose taking 0000 as new focal technology. Agent 2 investigates 0110 ($F = 0.37$) and 0101 ($F = 0.48$) and proposes taking 0101. So, where agent 1 got stuck in the branch of 0000 and where agent 2 would have selected 0110 based on F_2, we see that the collective now picks 0101 as new focal technology. Agent 1 will now inspect 1101 ($F = 0.47$) and 0001 ($F = 0.49$) and propose 0001 as new focal technology. Agent 2 will inspect 0111 ($F = 0.60$) and 0100 ($F = 0.24$). The collective will now of course select 0111 to start from. We see that agent 1 will inspect 1111 ($F = 0.61$) and 0011 ($F = 0.56$), while agent 2 inspects 0101 ($F = 0.48$) and 0110 ($F = 0.37$). A new round will prove that nor agent 1, nor agent 2 can improve technology 1111. In fact, the collaborating agents have now found the global optimum (by accident by the way, because despite that the joint expertise covers the whole search landscape, the agents might still get stuck in a local optimum). We also see that this global optimum is not equal to the Simonian global optima according to the fields of expertise E_1 and E_2.

Operational advantages of collaboration and their interpretation

By interpreting the events in the example and further reasoning about what actually is at stake, we see that in this model, collaboration of agents with disjoint fields of expertise has six obvious advantages:

- The collective generates more technologies,
- selects a new focal technology from a larger set of candidates,
- hence has (in expectation) more fit technologies eligible to enter the market.
- The agents furthermore have a more accurate fitness assessment $F(T, E_i \bigcup E_j)$, which makes
- search decisions more externally valid (i.e. with respect to global fitness) and, hence, the *global* fitness of the final technologies (in expectation) higher.
- Agents can pull one another from (Simonian) basins of attraction of what the collective assesses as a (myopic) poor optimum.

If there is (some) overlap in fields of expertise (and the conjoint fields of expertise do not cover the whole search area, i.e. $|E_i \bigcup E_j| \neq N$), these advantages become less significant. After all, a part of the considered mutations is evaluated by *both* agents, so fewer technologies are generated and the focal technology hence is selected from a smaller set. As such, there are fewer technologies evaluated before ending up in the optimum and therefore the fitness is less - in expectation. Furthermore, the additional accuracy in assessing fitness is less substantial and therefore the search decisions are less accurate. The eventually obtained technologies are therefore expected to be less fit.

We will now shortly halt to provide an interpretation of the operational definition of collaboration and its operational advantages in terms of the TCE concepts.
Working with $E_i \bigcup E_j$ is sharing knowledge on the value of particular elements and as such informing one another of the actual inferences of elements across the boundaries of the disciplines of one another. By sharing expertise in assessing the fitness, collaboration becomes more than outsourcing with a loosely defined interface. Agents actually share ideas of how to continue the innovation trajectory, informing about particular 'no-goes' in development and thereby forestall ending up in pockets of technologies with poor fitness.

If we look closer into the set of mutations evaluated each iteration, we notice that the collective actually is a *super-agent* with expertise $E_i \bigcup E_j$; due to the fact that the flip concerns only one element at a time the collective investigates the same mutations and with the same expertise. Eventually, both agents enjoy the benefits of the technology jointly produced. The knowledge and expertise then is embodied in the technology string. This can be perceived as transferring knowledge. The main question now is whether we can use the breadth of expertise to operationalize the TCE factor *complementarity*. Recall that we discerned two dimensions for complementarity: the relative contribution to scope of control and the interdependency of the scopes of control of the agents. As far as the last dimension goes: due to the random assignment of fitness interdependencies, the technological interdependency is evenly distributed across elements. So, the parameter K also determines the interdependency of agents, given their scopes of control, in innovation performance. As far as the first dimension (the relative contribution to the scope of control) concerns: the larger the contribution of additional control with respect to the search space size $|E_j \setminus E_i|/N$, the more attractive that collaborator E_j becomes to agent E_i. Let us associate this scope of control with E (and $|E_j| = |E_i| = E$), then complementarity is strongly related to E. In section 2.3, we already observed that complementarity is high if the scope of control (i.e. the span of competencies related to the disciplines the firm is specialized in) is intermediate and the interdependency is considerable. We also observed that complementarity is low if either the scope of control spans about the whole search space (the relative contribution must be low) or the interdependency is low (there is no synergistic advantage to be enjoyed). In our operationalization we see that also N is at stake.
If the scope of control is very limited ($E \ll N/2$), the actual innovation improvement is moderate as the collective still suffers from limited capacities. Yet, if the scope of control is moderate ($E \gg 0$ but $E < N/2$) to considerable ($E \approx N/2$), the actual contribution of control is valuable, especially if $K \gg 0$ as the additional control enables each of the agents to escape poor basins of attraction and prevent being locked in at a poor optimum. If the scope becomes large ($E \gg N/2$ but $E \leq N$ of course), then the actual contribution of control begins to drop (as $|E_j \setminus E_j|$ becomes smaller). So, if $E \approx N/2$, then the actual contribution is most effective (as the collective controls about the whole search space), while if E either increases or decreases, the actual contribution decreases. If E is large however, the reason lies in the fact that the agent alone has a rather decent innovation performance, while if E is small, the reason lies in the fact that the collective still has a rather poor innovation performance!
We see that we are well capable to explain the operational advantages of complementary knowledge as formulated in our discussion of complementarity in subsection 2.3.1.

Although we have now defined collaboration at an operational level and evaluated the operational advantages, we will see in subsection 5.4.1 that the real evolutionary benefit is not the increase in fitness, but rather in something we call the innovation performance augmentation. In that subsection, we will translate fitness into payoff through the (non-linear) market function. From the fact that agents have to share this payoff, it becomes obvious that obtaining just a higher fitness is not enough, but that the increase in fitness and thereby in payoff per capita should be high enough to justify collaborating.

5.2.3 Experimentation landscape features and operationalization of the conceptual model

Apart from the conception of technology and the conception of the innovation process, the technology landscape search model has yet a third dimension: the experimentation landscape features. Although that technology landscapes often simply are there to reflect uncertainty of innovation outcome, sometimes landscapes are designed in order to introduce some feature into the operational innovation process to discern the effects of that feature on the emerging strategy (e.g. complexity on collaboration propensity, cumulative structure of skills on search behavior).
In our case, we have adopted the NK landscape as our technology landscape to introduce complexity K into the innovation process. We have also seen that we can immediately operationalize the TCE factor complementarity by introducing the field of expertise of agents.

5.2.4 Evaluation of technology landscape search

Here, we evaluate the just described technology landscape search as core for our Neo-Schumpeterian model of R&D collaboration.
We will first stipulate several advantages of grafting our landscape model firmly onto the NK ~~landscape. These primarily concern the ease with which we can operationalize our TCE factors.~~
We will then touch upon properties of the NK landscape and show that we have to overcome some features of search in order to prevent introducing artifacts for innovation. We will also show that our definition of technological complexity as formulated in section 1.3 is not completely met. We will also make plausible that our conception of innovation is too limited and that Simonian innovation perhaps is not just trial-and-error.

Let us first look at the clear advantages of adopting the Kauffman NK technology landscape search. There are three points. Firstly, it allows immediate incorporation of several conceptual variables. We can use K to tune the complexity (extent of interdependency of elements) manifesting itself in ruggedness of the fitness over the landscape. Our myopic search heuristics entails technological uncertainty and introducing a 'patch' concept allows for straightforward implementation of the complementarity concept. Furthermore, the fact that technology is a unique instance of a binary string facilitates introduction of exchange, spillover and reverse engineering of technology. This contrasts the common mere displacement in production function parameter space or capability vector and also allows an immediate implementation of the spillover so prominent in the conceptual framework.
Secondly, as hinted in section 2.2, Simon argues that firms conduct local trial-and-error. This obviously is also implemented by non-global and restricted search. As a matter of fact, most of the restrictions formulated in the Simon (1955) paper are met immediately! A. An agent has imperfect foresight, as it cannot forecast values and cannot forecast whether it is heading for a poor optimum or not. B. An agent suffers bounded rationality as it is only capable to follow a hill-climber algorithm and does not create a mapping of the underlying technological interdependencies (which would in fact allow it to *engineer* a fit solution purposefully). C. An agent also suffers imperfect assessment of the true value as we have the agent follow its Simonian fitness criterion $F(T, E)$. D. An agent cannot control all of the variables of the technology as it is confined to its expertise patch E of the landscape.
Thirdly, the modeling of technology as a multidimensional configuration instance consisting of product, process, service and managerial elements, codified as a unique Boolean string is not just appealing but also allows technological progression being conceived as the comprehensive Schumpeterian innovation. The conceptual richness is pleasant as we can simply codify everything of relevance to the 'market performance' of an agent that is not explicitly incorporated in the Neo-Schumpeterian model.

One of the downsides of using the NK landscape is that we have to limit our conception of innovation. Recall from the outline in section 5.1 that each agent invents or reverse engineers exactly one technology each period. The agent furthermore is involved in exactly one project and the agent will finish that project that same period. An agent will incur no costs for invention, reverse engineering or innovation. All agents however incur the same *fixed* costs C each period. These limitations are somewhat peculiar at first sight, but scholars familiar with NK landscape know that we might indeed be looking at artifacts of the search trial properties. Search trail length is distributed as the logarithm with base 2 of $K+1$ if $0 < K < N-1$, and, so, the search trail is longer if K is lower. Adding costs for each improvement would hence mean that the total expenditure on an R&D project is higher if K decreases and that (given a fixed budget) less technologies would be finalized and brought to the market. We have found little (empirical) support for these search trail characteristics. Are innovation trails for simple technologies really longer than for complex technologies? Intuitively, we expect the opposite! We therefore decided to single out these effects of K by providing each agent with a free invention or reverse engineered technology each period and having agents finish the project the same period. We also made search free and rather introduced fixed periodic costs C that are independent of K. By doing so, we were able to refrain from having to introduce investment heuristics and thereby keep the agent's search strategy simple.
Closely related is that -at an operational level- singular search and hill-climbing is not a realistic representation of innovation. We will just name three issues. First of all, not every element is equally important. This has both a functional as well as a subjective dimension. Some elements are central in the design as they have many interconnections with other elements (e.g. coachwork of a car), while other elements can be added without affecting the performance of the technology at all (e.g. color of a car). Some elements might or might not be functionality important, but apart from that might be considered (un)important by customers. Note that this will allow a sort of weighted search by starting out looking at changing only the important elements. Second of all, engineers will generally pay attention to the changes that particular changes bring about elsewhere and thus create a sort of mental map of the technological interdependencies. This will allow them to improve elements purposefully and not just 'trial-and-error'. Third of all, due to differences in the number of relationships and presence of 'central' elements, there are 'natural' clusters of elements. Engineers are likely to isolate such clusters and subsequently focus on increasing the performance of such components. By agreeing on 'standard interfaces' between such components and optimizing those components, the search space gets aggregated as such components can be fitted in closely related technology instances as long as the standard interfaces are respected. An interesting example is the development of the separate condenser by James Watt that allowed researchers to simply introduce this standard technology and to focus on different issues (See Frenken and Nuvolari, 2003).
Due to our limited conception of R&D capabilities, and especially the fact that it is a brainless heuristic rather than engineering using a R&D knowledge base, the complementarity primarily lies in operational rather than strategic advantages (e.g. learning, exchanging engineering knowledge).

Another downside is that this technology landscape -like any other landscape is expected to do- does not meet up with the definitions.
Recall from section 1.3 that we conceive technology as a hierarchy of components consisting of elements, where elements within and across components are functionally interrelated. We see that we meet this description only to some extent. We have no hierarchy of components, although one might argue that this is obviated by simply concatenating the components specifications to one long string. We however do not have components as all elements are (on average) equally connected.
Furthermore, if we hark back to the definition of complexity as provided in section 1.3, we see however that we do not meet all five dimensions! Our operationalization only meets the dimension related to the number of elements and the intricacy of the relationships. We however acknowledge that although the NK landscape is not explicitly subdivided into separate, hierarchically

ordered components, a purposeful layout of technological interdependencies does allow mimicking that without problem and hence meeting that dimension too. We see that we then might also meet the closely related dimension of the diversity of disciplines in that way, especially with introduction of the notion of fields of expertise.
We however fail to incorporate the dimension of (non-)decomposability, and particularly fail to meet the property that technological elements are linked together delicately. We hence fail to model that technology is likely to malfunction completely if tampered with and that it is very difficult to recreate technology with the same properties from different elements. The common observation is that more complex technology is more vulnerable; small changes might bring about severe drops in performance or even complete malfunctioning. Here, however, performance of technology is operationalized as the arithmetic mean of the fitness value of the individual elements, the 'malfunctioning' of a single component has only limited impact on the overall performance, especially if N is large (the variance decreases). Furthermore, for large K (and large N) nearly all technologies have about equal fitness, so tweaking individual elements brings at most a small dent in fitness value (vis-à-vis the drop in fitness for lower K)! In appendix A we reveal the basic properties of this phenomenon known as the complexity catastrophe (Also see Kauffman, 1993). We will see that this property will affect our results and we will hence return to this topic later.
The operationalization of complexity also lacks 'specificity of knowledge' or 'maturation' properties. ~~Due to the 'instance' nature of technology (the fact that we have 2^N instances and no engineering~~ knowledge base of the underlying relationships), each technology does not have an a priori relationship with earlier search trials. Agents simply follow the same heuristic over again. Ordinarily particular engineering information (like: 'use the separate condenser when building a steam engine') becomes generally, publicly available knowledge when technology matures. Accumulation of technological knowledge makes that engineers can revert to technology already there without have to 'reinvent the wheel'.

Let us shortly recapitulate what we just discussed. We have seen that modeling R&D as NK technology landscape search has several clear advantages. We can immediately provide our TCE factors complexity and complementarity with an operationalization that -in appearance- relates to the operational definitions of technology and technological complexity provided in section 1.3. We furthermore meet the Simonian specification of human search behavior. The instance nature of technology appears to allow straightforward introduction of spillover as well as technological progress. We will see in subsection 5.4.3 that this operationalization of spillover is (too) limited, regretfully.
The disadvantages however also are considerable. Upon adopting the NK landscape search, we introduce artifacts related to search trial length which we have had to find a workaround for. A closely related point we discussed concerned the -in our minds- poor operationalization of real engineering practices. We argue that R&D engineers generally search in a weighed manner, thereby construct a mental map of technological interdependencies and eventually (collectively) aggregate the search space.
We also see that if we take the broad conception of technological complexity, that we do not meet the two dimensions of decomposability and specificity/ maturity. As far as non-decomposability goes, we see that the fitness measure of technology behaves differently upon tweaking technological elements then does performance. We will see later that the excess of the fitness measure behavior known as the complexity catastrophe phenomenon plays a prominent role in our model and explains much of the behavior we will observe in the simulation data. We have argued that cumulation of technological knowledge (and in fact the underexposed nature of engineering knowledge) and standardization is not present.
Our list of pros and cons is certainly not exhaustive, but we believe to have covered the most salient ones. For the moment, we will leave the implications of the shortcomings for what they are (we

will not redesign the technology landscape search model – we will leave that for follow-up studies). Especially in section 7.3 will evaluate the extent to which any of these issues has affected the results eventually obtained.

5.3 R&D project configuration matching

In subsection 5.2.2, we have seen how collaborative innovation is defined as an iterative search-and-jump with shared expertise. We however have yet to explain how agents decide if and -if so- with whom to collaborate. We will now first shortly describe our idea of how firms do find potential collaborators in practice and how we have had to restrict our own implementation thereof and justify for those restrictions. We then operationally define the matching algorithm we designed. After that, we will shortly discuss the basic properties of this algorithm.

5.3.1 Preliminary restrictions posed on our matching algorithm

In reality, potential R&D collaboration partners usually find each other among the circle of suppliers and customers, public research institutes or competitors and specifically those economic actors of which the principal firm thinks that they will help achieving (strategic) goals. These goals obviously relate to the motives discerned earlier which typically are contribution of complementary knowledge, providing access to particular markets (either technological or geographical distant), et cetera. If we limit ourselves to a single firm looking for contribution of complementary, technological knowledge, then this firm is expected to scan its environment for firms using a criterion that is a proxy or estimation of the innovation performance that is expected to be achieved. Such criteria typically take the form of having particular research facilities, technological know-how, expertise in auxiliary techniques, complementary assets, et cetera.

In an early version of this simulation model, we had several matching criteria, including measures on the union, complement and intersection of the fields of expertise, past innovation performance in terms of the jointly generated payoff and the market position of the potential partner. We however discovered that the exerted evolutionary forces were weak and the strategy parameters were insufficiently conditioned. This yielded simulation results with considerable variance and absence of convergence. We decided to drastically reduce the collaboration matching heuristic and take the actual preliminary suggested amendment to a proposed R&D project starting point as a proxy for the agent to estimate the attractiveness of collaborating with a particular potential collaborator.

In reality, firms certainly do not consult all potential partners, and not just because of high contact costs. Most of these candidates can be precluded quite early. As we however do not want to further complicate the model by introducing proximity measures or agent characteristic to be used on non-linear, agent-based level for preliminary preclusion, we have introduced a top-down procedure to determine the R&D project 'configurations' taking the form of either a pair of two agents or an indication that the agent will work solo.

We now have a simplified attractiveness appraisal criterion, a simplified preselection device and a top-down matching procedure. The algorithm revolves around an appraisal criterion based on the change in fitness by amendments (which is a proxy for expected innovation performance increase), a preselection based on this change in fitness and then the determination of the actual configurations based on an ordering of the fitness of the R&D project starting technology.

5.3.2 Operational definition of the matching algorithm

Recall that at the start of a period, all agents receive a newly generated technology (invention) or (with probability ρ) a reverse engineered technology already on the market. The algorithm defined here is now based on the ranking of these 'configurations' (pairs of agents) based on the fitness of technology that is obtained by having agents improve/ alter the new technology of one another based on their respective top-fit technologies. However, not all collaboration configurations are considered: only those for which the amendments bring about a change in fitness that is acceptable to both agents. An agent finds a change in fitness acceptable if this change exceeds its δ value. This delta as such closely relates the 'eagerness to collaborate'. Eventually, by a simple top-down selection rule, a matching is obtained that specifies which agents collaborate and which agents will work solo.

Let us now define what this top-fit technology then is, and describe such an alteration operation. We will then describe how each agent decides which technology he will propose to candidate collaborators and how candidate collaborators come to a possible improvement. Next, we will describe how the agents decide with whom collaboration is preferred and show that if they follow a simple decision rule they will establish a Pareto optimal solution. Eventually we stipulate some properties of the algorithm.

Firstly, we define a top technology T^*_{it} as the fittest technology according to $F(T, E_i)$ that agent i has yet encountered until (but excluding) period t. From the use of the fitness measure $F(T, E_i)$ as criterion, this technology is top-fit *relative to the expertise* E_i of agent i. We will have the agents use this Simonian top technology to reflect that agents simply are not able to assess the absolute, global value of their technology as they suffer bounded rationality and imperfect information.

Secondly, we introduce a concept of a first, intuitive improvement operation upon technology, which simply is replacing elements in the unaltered technology with elements in the top-fit technology. An agent of course only replaces items within its level of expertise. Note that this is the best -from the agent his point-of-view- the agent can do, after all, the agent has not yet found a better technology based on its imperfect fitness assessment $F(T, E)$!
Let us formalize this 'cross-fertilization' operation by introducing the recombination operator $\otimes$: $\mathbb{B}^N \times \mathbb{B}^N \times E \rightarrow \mathbb{B}^N$ taking two technologies and a set of indices as input (representing the field of expertise) and a technology as output. $T_1 \otimes_E T_2$ is defined element-wise as:

$$T[i] \leftarrow \begin{cases} T_2[i] & \text{if } i \in E \\ T_1[i] & \text{else} \end{cases} \tag{5.7}$$

The output technology indeed can be seen as technology T_1 where elements are replaced with elements in technology T_2 if these elements fall within the field of expertise E. We will use this operator to reflect that if an agent suggests a change to technology, he will typically -boundedly rational as he is- replace the elements of which he knows that they yield him his (Simonian) top-fit technology.

Thirdly, let us now describe the matching procedure from the perspective of agent i. This matching procedure consists of: first of all, selection of the best starting point by the principal agent, second of all, requesting improvement proposals from all other agents, third of all, determining acceptance of the project (improvement) proposal, and last of all, determining the configurations (collaboration matchings and 'working solo' indications).
First of all, agent i has obtained an invention/ reverse engineered new technology T^I_i and is looking for a starting point T^P_i for its R&D project. Agent i will now first assess the effect of recombining it with its top-fit technology T^*_i to form the technology $T^I_i \otimes_{E_i} T^*_i$. The agent will now proceed with the most fit technology T^P_i of the two, i.e. will proceed with $T^P_i = T^I_i \otimes_{E_i} T^*_i$ if $F(T^I_i, E_i) < F(T^I_i \otimes_{E_i} T^*_i, E_i)$ or with $T^P_i = T^I_i$ otherwise. So, if the recombination brings about an increase in fitness, the agent will take that technology as a starting point for the R&D project, and otherwise will stick with the original technology.
Second of all, agent i will now request all agents $j \in A \setminus \{i\}$ to suggest an alteration to its starting point technology T^P_i by recombining it with agent j its top-technology T^*_j and thus to form technology $T^P_i \otimes_{E_j} T^*_j$. By doing so, agent j hence suggests an alteration (amendment) to

the proposed project starting technology. The agents i and j will then together (by joining their fields of expertise to form $E_i \bigcup E_j$) determine the fitness of the newly obtained output technology $F_{ij} := F(T_i^P \otimes_{E_j} T_j^*, E_i \bigcup E_j)$ and the fitness change $\Delta_{ij} := F_{ij} - F(T_i^P, E_i)$ thus established. This procedure is followed for all agents and we thus obtain a Δ matrix containing the $|A| \cdot (|A| - 1)$ fitness change values. Of course $\Delta_{ij} \neq \Delta_{ji}$.
Third of all, at this stage, the agent collaboration strategy parameter δ comes into play. This parameter expresses what an agent accepts as a fitness improvement of a technological change suggested by another agent to the technology with which a new R&D project starts. If $\delta > 0$, the agent thus requires this change to bring about an increase in fitness, if $\delta < 0$, the agent settles even with a decrease in fitness, which can be interpreted as that the agent is eager to collaborate. As such we can simply review all elements Δ_{ij} and if $\Delta_{ij} < \max(\delta_i, \delta_j)$, the configuration $\{i, j\}$ is excluded immediately since for either one of the agents the fitness change is not acceptable. This process reflects the pre(de)selection of collaboration candidates.
Last of all, following this procedure, we can construct a set for each agent i that contains collaboration configurations (the index of the candidate collaborators) that are acceptable to both agent i and the candidate collaborators contained in this set. We now assume that agent i wants to collaborate with the agent j with which it produces the most fit technology, i.e. the collaboration with the maximum F_{ij}. Note that we here slightly violate the satisficing property of agents for our matching algorithm to work. It is important to realize that if all agents are determined to stick to the configuration with the highest fitness value, there is a simple solution. If F_{ij} has the (globally) highest value (and the matching is still available), then agent i and j will definitely stick with that option. All other agents will have to pick a configuration not involving agent i and j and for those agents the same story applies. So, by subsequently picking the configuration with the highest fitness value F_{ij} and excluding the agents in that configuration for further consideration, we obtain *the* solution. Note that this solution is *Pareto optimal* as no agent can improve its solution without causing another agent to have to pick another solution that is not the best possible for that other agent.

5.3.3 Properties of the matching algorithm

We will now stipulate some properties of this matching algorithm. Four issues catch the eye. Firstly, if agents do not have the same field of expertise (and hence $|E_i \bigcup E_j| > |E_i|$), the variance of $F(T_i^P \otimes_{E_j} T_j^*, E_i \bigcup E_j)$ is smaller than that of $F(T_i^P, E_i)$. The fitness value is then expected to be closer to the mean (1/2). Although the fitness of a *random* point on the landscape can be approximated by a Normal distribution with mean 1/2 and variance[1] $1/(12N)$ (Skellett et al., 2005), the fitness of our technologies T_i^P and $T_i^P \otimes_{E_j} T_j^*$ do certainly *not* have an expected value of 1/2 as these technologies have been recombined with top-fit technologies. The question now is: can we say something about Δ_{ij} already? The higher the initial fitness, the less likely it is that there really is an improvement in fitness, especially if K increases. Even if the fitness stays the same, the assessment with the conjoint field of expertise is in expectation closer to 1/2 than is the original value. So, all in all, we expect Δ_{ij} to be (slightly) negative, on average, but we also expect some of the scattered values to be positive.
Secondly, due to the use of δ in this algorithm, 'collaborative' agents (low or negative δ) display reciprocal complaisance. Such a collaborative agent accepts both a (slight) performance hit in a project proposed by itself, but also agrees working on a poorly fit project proposed by another agent and hereby thus helping the proposing agent!
Thirdly, since we determine a matching top-down, we obtain a different solution than if we would have picked agents at random and would have let them select their preferred partner, i.e. a sort of

1. Note that the variance is independent of K since it is a random point and we do not consider the relationship with any other point. The N fitness contributions are in fact N draws from the standard uniform distribution.

first-come-first-served system.
Fourthly, the first selection of configurations is based on Δ_{ij}, which of course is expected to be larger if the initial technology has poor fitness and hence selected by the agents sooner. On the other hand, the second selection is based on the actual fitness of the finally obtained starting technology, which seems to filter out the project starting technologies with poor fitness.

Interpreting this matching algorithm within the TCE framework, we see that the principal firm shows preference for the candidate collaborator whose proposed technological change immediately brings about the biggest, accepted change in (Simonian) fitness, i.e. who immediately brings about the biggest reduction in technological uncertainty. If we furthermore adopt the 'comprehensive' technology conception and argue that market factors are also (partially) encoded in the technology string, then we are talking about the biggest reduction in the compound uncertainty in returns resulting from both R&D and market practices. As we will see in the next section in which we present the market model, we indeed see that we better talk of uncertainty in returns from R&D.

5.4 Market, payoff and patenting

In section 5.2, we have defined the core of our Neo-Schumpeterian model, i.e. the R&D (collaboration) activity/ behavior. The landscape search model in fact is a fundamental model of R&D collaboration and would allow us to conduct studies as described in subsection 3.1.2. We however are interested in emergent properties and will as such frame this 'fundamental' core search model within a Neo-Schumpeterian, evolutionary framework. To that end, we will introduce the market, entry (imitation), capital stock and exit (deselection) components into the operational model. Although we have already operationalized TCE factors *complementarity* and *complexity* in our core technology landscape search model, the expansion we will allow us to also operationalize the TCE factors *appropriability* and *level of competition.*

Introduction of a market as a selection device (as opted by Alchian) is compulsory for a genuine Neo-Schumpeterian model. In subsection 5.4.1, we will introduce an operational market model to translate the innovation output (as a product of an R&D strategy) to payoff (as a measure of strategy performance). This payoff will contribute to capital stock, and, as we will later see, thereby chances of survival and propagation of the strategy followed. The underlying presumption hence is that the performance of the vehicle of a strategy (the agent) depends 'sufficiently' strong on the R&D collaboration strategy such that selecting agents on the basis of their performance actually also selects the 'best' collaboration strategy.
As already hinted before, we can simply use the ordinal fitness values to attribute payoff. Due to the comprehensive technology concept (see the definitions in section 1.3), fitness $F(T)$ of a technology T is associated with better *overall* performance (a net improvement in returns due to e.g. better marketing, more efficient production, better quality/ quantity, meeting consumer preference better, selling more) and higher payoff. The concept of a 'market' at which different of such comprehensive technology recipes compete can still be used to translate technology fitness into payoff.
In order to operationalize appropriability, we will introduce the concept of a 'patent' in subsection 5.4.2. From the exposition of appropriability in subsection 2.3.1, we know that instruments for appropriation generally protect the originator of leaked technological or innovation engineering knowledge against opportunistic use. In order to complement our operationalization of appropriation, we will introduce the reader to the operational forms of spillover and externalities in this Neo-Schumpeterian model in subsection 5.4.3.

5.4.1 Operational market model

In order to keep the model simple, we have decided to not bother about introducing customers and their preferences, but to simply aggregate the demand side into a single payoff function $R(T)$. We will now first introduce our conception of the market and the payoff function and its parameters, then give a short example of what kind of payoff to expect dependent on model parameters and finally to return to economic justification of the use of the payoff function.

The set of marketed technologies and the technology payoff

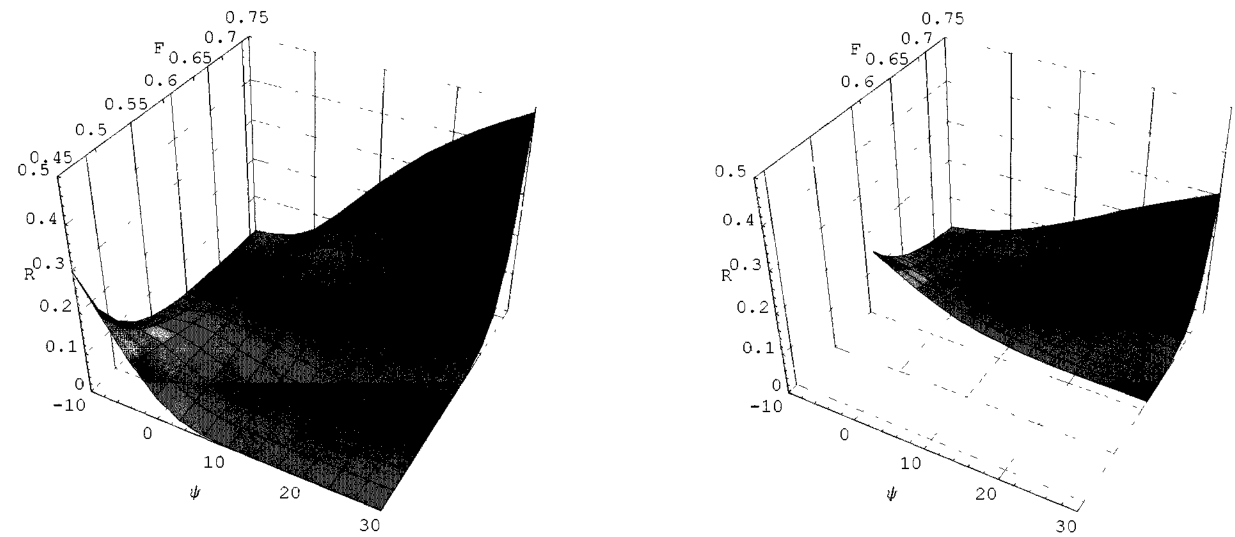
First, let us introduce the demand market. In reality, newer designs of products gradually replace older designs as these newer designs meet preferences better and/or are technologically superior and/or economically more interesting for the producers. In odd cases some select group of consumers persists in using old designs for sentimental reasons, e.g. people restoring old-timers, or simply sticking with it as it is technically still operational, but manufacturers most often stop producing the outdated technology. It however is more or less rule that producers switch to making and consumers switch to buying the new technology (be it stimulated by marketing).
Let us say that fitness of technology $F(T)$ reflects the level of this compound performance for the producing agent. The payoff $R(T)$ for technology T is based on its fitness $F(T)$ relative to the fitness of other technologies on the market. All agents launch their technology on the same global market, no matter what field of expertise they have, which can contain up to M technologies. As all agents thereby compete for the same payoff, agents are direct competitors of each other. This set of M technologies gradually improves in terms of max, min and average fitness as technologies of poor fitness are pushed off the market by technologies with better fitness. As such we also see the set of technologies on the market as the technology frontier.
We also limit the number of technologies each agent can bring to the market to L technologies to reflect the limited production capacity of each of the agents. This also further levels the playing field such that performance (in terms of payoff) reflects the viability of the R&D strategy. A single technology can furthermore be brought to the market by multiple agents. First of all, because agents jointly develop particular technology. Second of all, because agents can by (accidental) invention, by reverse engineering or by collaboration end up with the same technology. This e.g. reflects the fact that dominant designs attracts multiple producers.
As we will see in section 5.6, agents are removed from the list of producers upon their exit. If there are no longer producers of a particular technology alive, the technology is removed from the market.

At the end of period t (when the payoff is calculated), the market contains a set of technologies $\mathbf{T}_t^m$ and agent i has technologies $\mathbf{T}_{it}^m \subseteq \mathbf{T}_t^m$ out on the market. Of course the number of technologies agent i markets is less than or equal to the number of technologies each of the agents can (or is allowed) to produce (i.e. $|\mathbf{T}_{it}^m| \leq L$). The set of agents 'selling' technology T at the end of period t is $m_t(T)$ and the number of agents obviously is $|m_t(T)| \geq 1$. The payoff R_{it} earned by agent i for having technology $T \in \mathbf{T}_{it}^m$ on the market during period t can be calculated from the *fitness* of this technology, $F(T)$, as follows (the formulation of this payoff function is inspired by that of Cattani and Winter (2004)) :

$$R_{it}(T) = D \cdot |m_t(T)|^{\xi} \cdot \frac{F(T)^{\psi}}{\sum_{T \in \mathbf{T}_t^m} F(T)^{\psi}} \tag{5.8}$$

Note that the right-hand-side does not depend on i, such that for two (different) agents i and j marketing technology T, $R_{jt}(T) = R_{it}(T) = R_t(T)$. The market will in total disburse $|m_t(T)| \cdot R_t(T)$ to the agents that market technology T.
The parameter ξ can be used to tune scale (dis)advantages. If $\xi = 0$, the payoff *per agent* does not depend on the number of suppliers. If $\xi > 0$, the more suppliers $m(T)$, the more payoff each of them receives, i.e. there are positive scale advantages. If $\xi = -1$, each supplier will receive a fraction $1/|m_t(T)|$ of the payoff that an agent would receive if he would be the only supplier. Note that if $\xi = -1$, the term $|m_t(T)| \cdot R_t(T)$ is independent of $|m_t(T)|$ (it compensates for the $|m_t(T)|^{\xi}$) and indeed no matter what the number of suppliers is, they share the single, fixed sum disbursed

by the market.
If $-1 < \xi < 0$, the fraction then received is more than proportional to the number of suppliers. One might argue there still is a synergistic, positive scale advantage. If $\xi < -1$, the fraction then received is less than proportional to the number of suppliers, i.e. there are negative scale advantages. Here, we will pick $\xi = -1$, i.e. agents receive a proportional part of the payoff.
Parameter ψ can be used to tune the 'preference for quality' (fitness), i.e. the 'tightness' parameter in the Cattani & Winter model. If $\psi = 1$, the 'raw' payoff (i.e. without scale-effects) of a technology T is exactly proportional to the fitness $F(T)$ relative to the fitness of all technologies on the market. If $0 \leq \psi \leq 1$, demand (total payoff) is relatively insensitive for difference in quality (fitness). If $\psi \gg 1$, demand shows a strong preference for high quality (fitness). Nota bene that if we adopt the 'comprehensive' conception of technology, then quality also encompasses process and service factors and the like. If the difference in fitness of the most and least fit technologies on the market ($F_{max} - F_{min}$) is small, ψ must be large to still have a strong 'tightness' effect. Here, we will pick $\psi = 5$, because in the beginning of the simulation run, the most and least fit technologies are wide apart, so we particularly promote agents that produce technology with relatively high fitness. The idea is that we hereby speed up exit of agents with inferior strategies and stimulate survival of agent with superior strategies. Upon progression of the technology frontier, the difference between most and least fit technologies decreases and thereby the tightness effect diminishes.



(a) Technologies with fitness values $\{0.45, 0.475, \ldots, 0.725, 0.75\}$

(b) Technologies with fitness values $\{0.6, 0.6125, \ldots, 0.7375, 0.75\}$

Figure 5.1: Plot of the basic return function for a market with 13 technologies with fitness values resembling either a 'broad' or a 'narrow' market (and $|m(T)| = 1$) for all technologies and $D = 1$

Examples of payoff for different distributions of fitness

Let us look at two examples showing us how much payoff is disbursed per period per technology as based on its (relative) fitness. From the two figures in 5.1, you get an idea of the effects of the 'tightness' (or rather quality preference) parameter on the basic return function. There are only 13 technologies on the market, with fitnesses equidistantly distributed over the F axis. In the left-hand side picture, the spread of the technologies is broad, while in the right-hand side, the spread of the technologies is narrow. The value on the R axis is the actual payoff that each of those technologies gets, for various ψ. For $\psi = 30$, the technology with the highest fitness receives the lion-share, while technology with the lowest fitness value receives (virtually) nothing.

We see that for a more tight market, the market shows a high level of 'quality preference' as it rewards top-fit technologies substantially more than it does technologies with poor fitness. Consequently, agents that follow R&D (collaboration) strategies that generate them technologies with relatively fit technologies have a higher chance of survival, and this chance further increases if the market becomes more tight.
If the fitness distance between the most and least fit technologies becomes smaller, the curve not only becomes more compact, but the absolute return for the top-fit technologies also drops. As soon as products have smaller differences in quality, the preference for quality is less in favor of high quality products.
We see that even for a tight market, once the technology frontier is more developed, the spread of technologies on the market becomes narrower and technologies compete more fiercely for the same payoff.

Innovation performance augmentation

The payoff disbursed by the market is a natural measure for innovation performance. Leaving the case where multiple agents that are not co-developers market the same technology, what now is the benefit of collaborating in R&D?

In subsection 5.2.2, we already indicated that innovating collaboratively generally yields optima with higher fitness. Let us have a look at a simple example for two agents. For clarity, we have depicted technologies, their fitness values (colored bars) and disbursed payoff (gray bar) in figure 5.2. Suppose we start out with technology T with fitness F. Let now agent 1 and 2 individually optimize this technology (according to their individual field of expertise E_1 and E_2 respectively) and say they obtain technology T_1^S with fitness F_1^S and T_2^S with fitness F_2^S respectively. First of all, note that F_i^S need not necessarily be higher than F. Since agents follow Simonian fitness assessments for guidance, this might even lead to a deterioration of the global fitness. If the initial fitness F is low this however is less likely to happen then when the initial fitness F is high.
If two agents collaborate and if the fields of expertise are completely disjoint and there is no (indirect) interaction between the fields of expertise, the agents can (at best) achieve the 'modular combination of components' T^M (with fitness F^M) when they collaborate. In practice, there usually is some interaction between the fields of expertise, and it is also likely there is some overlap. Due to this, the collective might be caught in a different basin of attraction leading to an optimum with lower global fitness and thereby end up in T_L^C, or they might help each other out of their respective poor basins and together obtain an optimum T_H^C with global fitness that is higher for at least one of the agents.
Depending on the parameters of the market return function provided in equation 5.8, the payoff for each of those technologies is something like we have depicted with the gray bars next to the fitness bars in 5.2. Clearly, the payoff per capita (i.e the dark gray parts of the gray bars) does not necessarily increase when collaborating, although the fitness does. The increase in fitness achieved by collaborating might only yield a moderate increase in payoff. Upon sharing the total payoff of this slightly fitter technology, there might be less payoff per capita than when keeping the total payoff of a slightly less fit technology. We indeed see that, although T_1^S is only modestly fit and less fit than T_L^C, R_1^S is clearly still more than R_L^C.
We now define the 'innovation performance augmentation' for principal agent i as the increase in payoff of the technology found together compared to the payoff of the technology found alone, i.e. $R^C - R_i^S$. It is likely that this increase is positive, especially if the initial fitness F is moderate to low and the breadth of the field of expertise is moderate to low. If there now furthermore is no overlap and no interaction, the eventually obtained technology will be the 'modular combination of components' (Something close to T^M). If there now is interaction (and possibly overlap), it is well possible the collective reaches an optimum with fitness higher than either one of them could

have reached alone, i.e. $F^C > \max\{F_1^S, F_2^S\}$ and especially if this technology is top-fit (relative to the state of the market at that time), it is likely that the non-linearity of the return function boosts the payoff and make the per capita payoff higher than the agents would have received alone $R^C > \max\{R_1^S, R_2^S\}$. This, for instance, is the case with technology T_H^C. We then talk of a *synergistic* innovation performance augmentation (and this of course is universal). It must be said that interaction between fields of expertise (and generally at least a non-zero K) is no guarantee for synergistic augmentations. Simonian fitness criteria in search occasionally makes the individual agents 'blind' for global fitness basins of attraction and thereby has them wander off into a Simonian fitness basin of attraction that eventually produces a technology with higher global fitness. In this paper, we will however associate collaboration in search on landscapes with moderate to high levels of complexity and non-top-fit starting technology with (potential) 'synergy' in innovation performance. In case the landscape has a low level of complexity, we expect some increase in performance, but attribute this to 'substitution of complementary components' and expect the performance to be less than the strict 'modular combination of best solutions'.

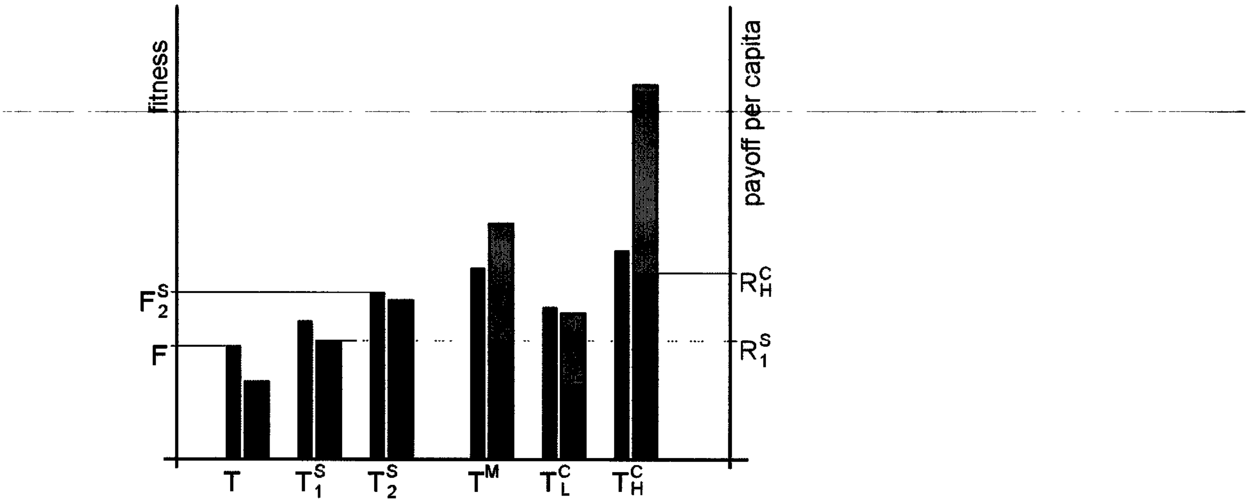


Figure 5.2: A graphical representation of the fitness values of and the payoff disbursed for marketing of the technologies we use to explain the innovation performance augmentation.

Interpretation and justification of the market model, implications for theory

We will now return to the interpretation and justification of our market model function.
We started this subsection by saying that we aggregated the consumptions into a demand market payoff, we however have to correct ourselves.
If we interpret the payoff function $R_t(T)$ as the *revenue* of sales of a particular product, there is an implicit assumption underlying the relationship between F and the payoff R (under the precondition that quality preference $\psi > 0$), which an economist will want to have clarified. Usually the returns R are calculated by multiplying the price p with the quantity Q sold. We however assume the price/ quantity decision to be codified in the technology string. The upward tendency (for $\psi > 0$) in figure 5.1 has the implicit assumption that $d\{p \cdot Q\}/dF > 0$. It is true that many economists do use the (commonly unchallenged) presumption that p increases with F, i.e. $dp/dF > 0$ (producing quality is more expensive and hence a higher price is asked to cover those expenses) and the presumption that $dQ/dp < 0$ (the demand drops if the price increases as fewer people are able or willing to pay for it). These presumptions however do not imply in any way that $d\{p \cdot Q\}/dF > 0$. In reality, it rather is not uncommon to produce a product of mediocre quality and to sell that at a medium price level, which allows to sell larger quantities and thus enables to generate a higher turnover R!

This practice is often fueled by scale advantages and thus higher profit margins (we are not talking about marginal profit margins!). If we are to pursue this avenue, we will have to introduce a market game or equilibrium assumption to determine Q and p.
If we rather perceive the payoff function $R_t(T)$ as the *profit* a firm generates from producing and selling a particular product, i.e. $R = p \cdot Q^s - c \cdot Q^p$, where there are certain costs to be subtracted from the aforementioned revenue in the form of the unit-cost c times the quantity Q^p of products produced. Note that the upward tendency (for $\psi > 0$) in figure 5.1 now has the implicit assumption that $d\{p \cdot Q^s - c \cdot Q^p\}/dF > 0$. It is furthermore important to notice that all of the terms p, c, Q^s and Q^p are none trivial functions. A technology T can now rightfully be referred to as a recipe for corporate arrangements and product features affecting (possibly) all of these four terms. There is no economic obstacle to assume that if $F(T) > F(T')$, we actually say $p(T) \cdot Q^s(T) - c(T) \cdot Q^p(T) > p(T') \cdot Q^s(T') - c(T') \cdot Q^p(T')$, i.e. fitness simply describes the profit and indeed the payoff curve can be strictly increasing in fitness.
We however need to go one step further to justify the market model function. As we will see in section 5.6, the actual capital stock accumulation per period due to agent activities consists of this payoff and the costs of conducting R&D (C). The expenses of conducting R&D are as such not accounted for in the term $c(T)$ in the profit equation mentioned the last paragraph. We see that we hence have to interpret this payoff as *returns from R&D* and that it as such reflects how much the producing firm receives by following the 'recipe' T for its processes, services, marketing and product features.
However, note that due to careful composition of the 'returns from R&D' $R(T)$ into the difference of gains and costs, these 'returns from R&D' can well account for issues like losses due an overproduction compared to demand, inefficiency losses suffered during production, et cetera. A more fit technology might as such also imply there is less overproduction or less inefficiency losses.

If we now hark back on our theoretic framework, we see that our market model will allow us to select agents based on their (accumulated) payoff and will as such allow us to establish the Alchian selection device. Zooming in on our TCE framework, we see that we can quite easily increase the factor *level of competition* by decreasing the total payoff D being disbursed periodically as well as increasing the tightness ψ of the market. In order to survive, agents will need to be more (dynamically) efficient. They have less periods to obtain top-fit technology and also really need top-fit technology to generate sufficient payoff. So, we see that the factor level of competition also strongly relates to the strength of the selection forces exerted on the agents.

5.4.2 Patents

In section 2.3, we already mentioned that absence of ways to protect own technology from imitation and copying forms a disincentive to conduct R&D as firms are then not able to recover costs of R&D. If we now return to our market model, we have chosen to set $\xi = -1$ in our market model and -as such- to have no positive or negative scale effects and to have agents share the payoff equally. If an agent discovers a top-fit technology and brings it to the market, other agents can imitate and reverse engineering this technology (or use spillover to own benefit). As these other agents then receive a proportional and fair share of the payoff, the agent that initially discovered the technology is insufficiently able to enjoy the returns of its efforts. As we have seen this theoretically discourages collaboration and even R&D in general. One immediately conceivable implication within our evolutionary framework is that this 'free-riding' might obscure the correlation of being able to generate top-fit technologies (and thus due to following a particular R&D strategy) and the performance in terms of capital stock development. So, the inability to sufficiently appropriate returns will hamper (or rather, weaken) selection forces and might thus result in unsuspected effects on and dispersion in the collaboration propensity measures.

In reality, means to protect from imitation are put in place to prolong the period in which the 'inventor' can enjoy monopolistic rents of its R&D efforts. Here, we will introduce *'patenting'* of technologies to hereby provide a mean to agents to appropriate the efforts of R&D by reaping the largest share of the payoff disbursed by the market. The idea is that upon bringing a technology to the market, (an) agent(s) can 'patent' this technology if it is not already infringing an existing 'patent'. During the running time of the patent, this patent will 'protect' the interests of the patent-owner by having imitators pay a license fee to the patent-owner. If technologies are imitated, patent-owners still get extraordinary, disproportionally high returns for some time.
Although we implement this 'appropriability opportunity' by means of something we will call a 'patent', this is purely nomenclature. A 'patent' can constitute a wide variety of phenomena, such as lead time advantages, geographic advantages, design complexity, trade secrets, lock-in of customers or brand preference.

So, where ordinarily the payoff for marketing technology T is the same for all agents, i.e. $R_{it}(T) = R_{jt}(T)$ for $i \neq j$, the actual payoff now depends on the status of the various agents involved. Let us define the new payoff function $R^P_{it}(T)$.
Define a 'patent' as a Hamming-neighborhood of size h around the technology being 'patented', i.e. the set of all technologies with Hamming distance less than or equal to h. Technology T infringes 'patent' P if T falls within the Hamming-neighborhood of patented technology T^P.
If a technology is brought to the market and *does not* infringe an existing patent, the agent files a patent which will be running for ω periods. If the technology has been discovered in collaboration, the agents share the patent (and the payoff). If a technology is brought to the market and it *does* infringe one or multiple patents, a share v of the payoff that would normally accrue to the marketing agent is now disbursed to the owner(s) of the patent(s).

Formally, this is implemented in a straightforward manner. Let $P(T)$ be the set of patents that are infringed by a technology T *at the time technology T is brought to the market.* This last addition is crucial as it prevents 'patents' being filed to entail license-fee claims on technologies marketed before that. Let then $a(p)$ be the set of agents that own the patent $p \in P(T)$ (and $|a(p)| \in \{1,2\}$ since the number of patent-holders cannot exceed 2). Each agent in $a(p)$ is said to have a share of $1/|a(p)|$ in the patent. Note that agent i can be owner of zero, one or more than one patent being infringed by technology T. Furthermore, let $k_i(T)$ be the total number of 'patent shares' agent i has (in total).

$$k_i(T) = \sum_{p \in P(T)} 1_{i \in a(p)}/|a(p)| \tag{5.9}$$

For each patent $p \in P(T)$, agent i receives $1/|a(p)|$ if it is patent holder, and receives 0 otherwise. This reflects that patent-holders equally share the license fees being paid. The total of shares the agents have should obviously equal the number of patents infringed:

$$k(T) = \sum_{i \in A} k_i(T) = \sum_{p \in P(T)} \sum_{i \in A} 1_{i \in a(p)}/|a(p)| = \sum_{p \in P(T)} 1 = |P(T)| \tag{5.10}$$

The actual payoff for marketing a technology (which is always under the umbrella of some patent!) can be calculated easily. The agents in $m_t(T)$ each receive $R_t(T)$, but each of them has to pay $vR_t(T)$ to patent-owners for license-fees, while each of them can keep $(1-v)R_t(T)$. Of this $vR_t(T)$ paid by each agent for license-fees, agent i receives a fraction $k_i(T)/k(T)$ for all of the patents it owns. This means that agent i receives $k_i(T)/k(T) \cdot vR_t(T) \cdot |m_t(T)|$ in total of all of the license fees paid for all of the patent shares it owns. Note that $k_i(T)$ can well be zero if the agent does not own a patent being infringed.
The amount disbursed to agent i for bringing technology T to the market given the patenting regime now becomes:

$$R^P_{it}(T) = R_t(T) \left\{ v|m_t(T)| \frac{k_i(T)}{k(T)} + (1-v) 1_{i \in m_t(T)} \right\} \tag{5.11}$$

The interpretation of this payoff R still coincides with the one devised in the last subsection.

If an agent exits, its claims on patents are lifted. After ω periods, the patent expires. If a patent has expired or all patent-holders have exited, then the patent is *not* removed from the patent administration, but turns into a 'patent-ghost'. If a technology is brought to the market that infringes the patent-ghost, the technology cannot be patented, but the agent marketing this technology will not have to pay any license-fees either. Note that an agent would otherwise be able to renew a patent, or an imitator would be able to file a patent concerning technology not invented by him. The patent-ghost is then there to account for the fact that particular advantages like lead-time and brand preference are transient and not renewable or transmittable. This patent-ghost artifact is thus enforcing some kind of system behavior by utilizing the existing implemented functionality in a way that is conceptually unaccounted for. Note that this patent-ghost then actually is a clear example of what Küppers and Lenhard (2005) would call 'partial autonomy' of the program.

If we now interpret this 'patent' concept in the light of our TCE model, we see that it functions as an operationalization of the factor *appropriability.* The extent to which agents can appropriate technology however is the same for all agents, i.e. both ω and v are the same for all agents. These parameters, as such, do allow us to increase the level of appropriability for the complete industrial sector. If we increase ω, agents can enjoy their monopolistic rents longer, while if v increases, agents enjoy higher license fees. As we will see in chapter 6, we have chosen to fix v and rather tune ω in the simulation runs to limit the parameter space.

5.4.3 Reverse Engineering and Spillover

In section 2.3, we observed that R&D (collaboration) propensity strongly depends on the degree to which technology leaks to collaborators or third parties (through spillover and externalities), the extent to which the use thereof by these competitors would be detrimental and the extent to which a firm can either guard itself against use or prevent suffering the financial consequence thereof. In the previous subsection, we have introduced the operationalization of the mean to appropriate the returns of R&D which restores the incentive to conduct R&D and engage in collaboration by overcoming the consequences of spillover and externalities. We thereby fulfill the need to operationalize the TCE factor *appropriability.*

In subsection 5.2.4, we argued that since we model technology as a unique landscape string (an instance), we can operationalize spillover by means of leaking instances. Here, we however argue that our concept of directed spillover is limited for two reasons. First of all, in early, exploratory simulation models we included spillover by means of transferring technology instances upon collaborating (we tried both just the string inspected upon conducting hill-climbing, but also tried sharing technologies in the direct vicinity of those inspected) which were then stored in 'technology repositories' of the agents. The benefit was that agents did not have to pay for examining technology strings (i.e. assessing fitness) already residing in the repository upon encountering a particular string again. For three different reasons we removed the repository concept. The effect of this exchange repository was rather insignificant because the probability of encountering exactly the same string was very small (in the order of 2^{-N} of course). Furthermore, the performance hit in the running time of simulations was dramatic. Due to later simplification of the cost structure, agents no longer paid for examining the string and hence there was no cost advantage any longer. Second of all, ordinarily, spillover particularly concerns information on how to engineer a product and the rationales to do it that way. The receiving party then saves both time and money to discover this how and why and can immediately progress from there. As the agents in our model do not have an innovation engineering capability (i.e. the knowing how to construct particular products to generate earnings), leaking of technology strings does not bring about an increase in innovation performance.

However, there is indirect, less obvious and 'non-adherent' spillover (in the sense that it is not adhering to management of R&D or any other corporate activities) which reflects in the technology produced in collaboration. First of all, spillover occurs upon cross-fertilizing technology that is taking as a starting point of collaborative R&D. Recall from section 5.3 that the starting point is $T_i^P \otimes_{E_j} T_j^*$ in which hence (possibly) part of the top-technology T_i^* of agent i and part of the top-technology T_j^* of agent j is utilized. It is very likely that part of this starting technology string is preserved in the final optimum. Second of all, there is 'non-adherent' spillover in the form of the 'knowledge' on fitness of technologies that is used in jointly achieving better, more fit optima.
If we acknowledge that these benefits of collaboration also are some distant form of 'spillover', we see that our appropriation instrument 'patenting' does in fact have a modest effect. Especially for top-fit starting points, the probability of ending up in the neighborhood of the top-fit technologies T_i^P and T_j^* is imaginable and hence having a patent on these technologies (that already are marketed) prevents the collaborator from enjoying such spillover. Recall that during the development of a mass-market upon emergence of dominant design, potential entrants are eager to collaborate with prominent players to quickly get to the technology required to produce the dominant design products. Our patenting concept would thus protect innovators from such opportunistic collaborators. Note furthermore, that upon starting from an invention, the probability of ending up in an existing patented technology is only considerable if the agents have considerable breadth of expertise E, collaborate and as such jointly span the largest part of the landscape and furthermore that K is low (otherwise the chance of ending up in a different peak is large).

We see that our operationalization of appropriability is somewhat limited as far as spillover is concerned, but not superfluous. If we realize that the concept of reverse engineering (already mentioned in the outline in section 5.1) in fact reflects spillover to all agents in the industry sector, i.e. what is know as externalities, it should be clear that appropriability in fact does effectively protect against such externalities.
In the operational model, we have parameter ρ to tune the probability that an agent will reverse engineering a (random) technology T^m already on the market rather than generate a technology anew to start an R&D project with. An agent i of whom the technology is reverse engineered hence leaks the technology instance to the copying agent j. There is a fair probability that the reverse engineering agent j will end up within the h Hamming-neighborhood of T^m and thereby infringe the patent of agent i. As such the patent will protect agent i from the negative consequences of externalities.
Several factors increase the chance of infringing the existing patent of the technology being reverse engineered or the patent of a closely related technology stemming from previous reverse engineering operations. This chance is bigger if agents have narrow breadth of expertise, work solo and if K is high (such that the agent is likely to end up in a strongly correlated peak nearby).

All in all, 'patenting' as a mean to appropriate is expected to have a modest effect if there is no reverse engineering (no externalities) as spillover then is very limited, but this effect is expected to become somewhat stronger the more progressed the technology frontier is. 'Patenting' however increases appropriation of returns from R&D if there is reverse engineering. We see that K and E are both expected to mediate the effect of appropriability as they affect the probability of infringing an existing patent.

5.5 Entry and strategy imitation as novelty

From the theory it became clear that entry and exit are *crucial* to a genuinely Neo-Schumpeterian model of an industry. We will shortly recapitulate the function of entry as described in the outline in section 5.1 in the evolutionary process. Not only does it prevent the population from dying out (as we opted for exit), but since we will have entrants (imperfectly) imitate an (elite) agent

already operative, it partially propagates traits of the elite (and thereby embodies accumulation of favorable mutations), but also introduces some (new) mutation and thereby keeps up variation. It goes without saying that an entrant that is better adapted to the environment and the society, and -especially relevant in economic settings- is able to cope with (dis)advantages of late entry, has a greater probability to survive and hence propagate its strategies, technologies and features.
It however remains to be seen what entry constitutes in the real-world economy. From Michael Porter we know there are many forces that determine the entry probability, but, to cut things short, entry predominantly reflects an economic belief; there is an (implicit) economically sound, but boundedly rational reason to enter the industry. An entrepreneur would make a firm enter, obviously, if the entrepreneur beliefs it is able to make a profit or serve continuity of the firm. This belief stems from the fact that the entrepreneur sees it can improve the technology constituting the industry to better serve a particular niche, or that the entrepreneur sees that incumbents make extraordinary profits while it can serve part of the customers, either by undercutting the current market prices with equivalent technology or by introducing an alternative technology.

It should be clear that entry in this sense touches the very heart of the Schumpeterian ideas of sources of industrial dynamics. How can we now bridge the concept of entry in Neo-Schumpeterian evolutionary process and the belief-based entry in the real-world economics? As we will see, we kill two birds with one stone: we will both operationally define the mechanism for entry in the model and establish a link with the real-world phenomenon for entry.

The agents in the current model are not able to assess fitness or 'forecast' potential profit of 'pilot' innovations prior to entry (to model them suffering imperfect knowledge and limited foresight). Potential entrants however monitor the market and wait for a moment the market conditions are favorable for entry. Given the idea that agents monitor the market, or more specifically an aggregate measure of the payoff each of the agents receives, the obvious next step is to use the market concentration as a measure of entry probability. Here, we will use the reciprocal Herfindahl index to determine the entry probability. We will go into that in detail in subsection 5.5.1.

Apart from determining *when* a new agent will enter, we also have to decide *what kind* of an agent enters. As mentioned, the agent is set to imitate an elite agent and thereby constitute accumulation of favorable mutations and variance. What now determines whether an agent is elite or not and how does the entrant pick one for imitation? Since we already decided that the potential entrant monitors the market and determines the market concentration from the payoff, we have decided to have a new entrant use the accumulated capital stock[2] of the agents already operational to determine whom to imitate. We will discuss that in subsection 5.5.2.

5.5.1 Herfindahl index and entry probability

Without further elaboration on the economics, we will define the Herfindahl index and we will then formulate the entry intensity by relating the calculated Herfindahl index to an entry probability. We will finally also shortly hint on the interpretation within the TCE framework.

Let us first describe the Herfindahl index. Recall that the ordinary Herfindahl index is high, i.e. the reciprocal index is low, if market concentration is high. If concentration is high, few parties have relatively great market power. It is assumed that the extra-ordinary profits (often associated with oligopolistic or even monopolistic markets) attract entrants (under the presumption that the market is not a natural monopoly, of course).
Here, the reciprocal Herfindahl index is calculated from the rewards disbursed to the agents. The

2. As a note on the side concerning the viability of the use of such measures, profit (payoff) and accumulated capital stock information is (usually) freely available in annual reports of firms.

idea is that market power reflects in the (total) payoff an agent receives. Suppose R_i with $i = 1, .., A$ is disbursed, then the (reciprocal) Herfindahl index becomes:

$$h = 1/\sum_{i=1}^{A}\left\{\frac{R_i}{\sum_{i=1}^{A} R_j}\right\}^2 \tag{5.12}$$

This reciprocal index h expresses how many firms the market would shed if they would have *equal* market power. Obviously, $1 \leq h \leq A$ for all possible configurations. Indeed, $h = A$ if $R_i = R$ for all i and $h \downarrow 1$ if the market becomes more concentrated.

If an entry brings about a leveling off of market shares, then h increases. If the entry however brings about a further asymmetry of market power, then h decreases. If read in isolation, this last sentence should raise some questions, but an entrant might immediately cooperate with a top player and jointly generate top fit technologies. This would indeed cause h to drop, especially if ψ is large.

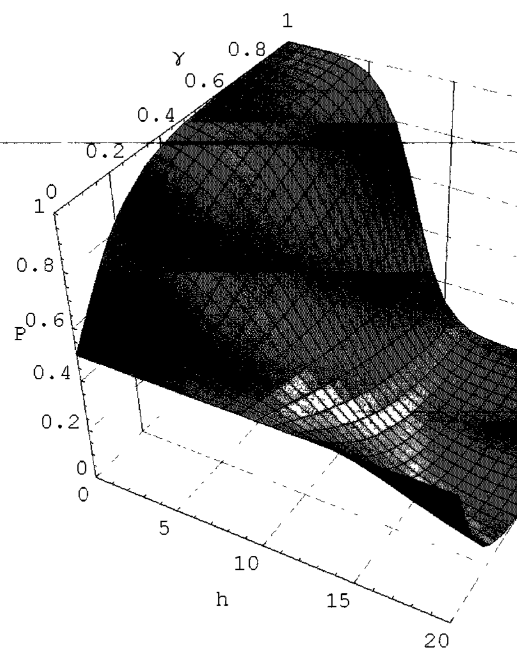


Figure 5.3: Plot of the entry probability function for $h_0 = 8$ and various values of γ

Let us now describe how we relate this Herfindahl index to entry intensity at an operational level. Each p periods, the Herfindahl index h and probability of entry $P_e(h)$ are recalculated and, then, with probability $P_e(h)$ a new agent enters the system. The probability of entry $P_e(h)$ should be higher if the reciprocal Herfindahl index h is lower. Rather than a crude Heaviside step function with $P_e(h) = 1$ if $h < h^*$ and $P_e(h) = 0$ otherwise, it is opted to use a (more natural) sigmoidal function. This would represent the fact that there is a different perception of the concentration, but, more importantly, firms differ in their (dynamic) efficiency and the perception thereof, and hence differ in what they (belief they) can realize under various conditions. Most firms only dare entering highly concentrated markets (low h) because there is a potentially large profit margin, while other firms even dare entering markets with low concentration (high h) as they are confident that they can attract enough customers on merits of the product and own managerial competences. Ideally, the sigmoidal function would allow us to tune the entry probability as a function of the concentration, and make the probability slowly decrease in a decrease in concentration (increase in h).

An (arbitrary) suitable candidate for a sigmoidal curve is the Richards (1959) growth curve, sometimes also referred to as the generic logistic growth curve (see Zwietering et al., 1990).

$$y = \frac{a}{\{1 + \nu e^{k(\tau - x)}\}^{1/\nu}} \tag{5.13}$$

By setting the asymptotic upper and lower boundary to 0 and 1, removing the deformation by ν and flipping the curve, the following 'decay' curve is obtained:

$$P_e(h) = \frac{1}{1 + e^{\gamma(h - h_0)}} \tag{5.14}$$

Parameter h_0 is the point of inflection, which is used to shift the curve over the h axis. If h_0 is high, the entry probability is high even for moderate to high h values. This means that potential entrants believe they stand a chance of surviving in a market with low concentration and many competitors.

Parameter γ is the decay rate which can be used to horizontally scale the drop. If γ is high (low), the curve drops steeply (gently). This means that there is a steep curbing of the probability of entry upon decreasing concentration, possibly due to oligopolistic characteristics of the market making it viable for only a low number of providers to operate on the market.

Figure 5.3 shows the probability as a function of h and γ.

What now is the interpretation of this entry intensity within our TCE framework? As said, the higher h, the lower the level of concentration, the more equally distributed the market shares and hence the fiercer the competition. As said, we can actually set the point of inflection h_0 as well as the drop scale γ, so we can actually shift and scale the entry intensity and thereby determine the rate of entry and, to some extent, how many agents are in the system. We can hence scale the fierceness of competition! So, we can use these parameters together with demand size D, market tightness ψ to manipulate the level of competition. As we will see, we have decided to fix these h_0 and γ parameters and rather use D, in order to limit the parameter space and thereby the number of parameters to simulate for.

5.5.2 Entrants and imitation

Now that we know when agents tend to enter and how to manipulate that, we still have to decide which agents an entrant will imitate. In the light of our Neo-Schumpeterian model, entry constitutes propagation (by imitation), accumulation and novelty (by mutation) of properties (here R&D collaboration strategy) that entail favorable features (here capital stock). We will now first explain what and how an entrant imitates of the agent it mimics and how it selects the agent being mimicked.

As far as imitation goes, we already hinted on the fact that the only 'strategy' that is copied concerns the 'eagerness to collaborate' δ (see section 5.3 for a description on how this strategy parameter is used), while the rest of the heuristics are exactly the same for all agents.

An entrant j copies the δ_i of the agent i it imitates, but makes an 'error' with a uniform distribution in $[-0.1; 0.1]$. So, $\delta_j \leftarrow \delta_i + \tau$, with $\tau \sim U[-0.1; 0.1]$. If $\delta_j < \delta_i$ ($\delta_j > \delta_i$), the preference toward working collaboratively (solo) increases.

If the change is favorable (in the sense that the entrant is superior to agents already in the system), imperfect imitation (by new entrants) propagates and optimizes the strategy further, otherwise deselection (by exit or exclusion from imitation) prevents propagation of the changes. Note that this principle allows the strategy population to 'tip over' to an alternative collaboration strategy.

As far as the selection of an agent to imitate by an entrant goes, we will be following the model of Tesfatsion & McFadzean (See Tesfatsion, 1998; McFadzean et al., 2001) and have entrants pick an elite agent having superior performance in terms of capital stock. This capital stock after all is accumulated payoff and hence a measure of the level of dynamic efficiency. By reversing the causal chain that payoff (or performance) is the outcome of a strategy, a firm that has managed to accumulate a lot of capital (and withstand competition) must have been performing well. Despite circumstantial conditions and coincidences, it is then argued that this is due to a superior strategy. As each agent is set to enter with a fixed capital stock Q^0, a simple 'score' can be devised. Agent i 'scores' $s_i \in \mathbb{R}$ (assumed unique, so no knots occur) based on capital stock and age:

$$s_i = (Q_{it} - Q^0)(t - t_{i0})^s \tag{5.15}$$

The first term, $Q_{it} - Q^0$, expresses the net change in capital stock over the lifespan of an agent. If an agent has top-fit technologies in a market with considerable payoff, Q_{it} can become very large. If an agent is close to bankruptcy, $Q_{it} - Q^0$ is likely to be negative. So, the $Q_{it} - Q^0$ measure expresses the extent to which a strategy has generated capital stock. The second term, $(t - t_{i0})^s$, is used to account for the actual lifespan. Variable s allows us to adjust the effect of the time an agent is already operational in the system on the score. For a fixed $Q_{it} - Q^0$, the score increases (decreases) with the number of periods an agent is operative if $s > 0$ ($s < 0$). For $s > 0$ ($s < 0$), the score expresses an appreciation for seniors (new rising stars). Here, we will set $s = 0$, so entrants are only concerned with the current cash balance of agents.

We now devise a ranking $\pi : \mathbb{R} \to \mathbb{N}$ based on the scores, with $\pi(i)$ being the rank of agent i. Obviously, if the rank of i is higher $\pi(i) < \pi(j)$, in the sense that i comes before agent j, then the score is higher $s_i > s_j$, i.e. the agent his capital stock performance (corrected for the appreciation of the time span in which this happened) is better. The best scoring agent simply is the agent with index $\pi^{-1}(1)$.

Using π we can, at any point in time, make a ranking from 'most successful' agent to 'least successful' agent. Evolutionary, the agent with the highest score, has the strategy that is most likely to survive, either through the lowest probability to perish, but also through the highest probability to propagate the properties. As hinted before, we will introduce propagation through imitation of the strategy (of a superior, high scoring, high ranked agent) by an entrant. So, here, an entrant will pick one of the $\lfloor \epsilon \cdot |A_t| \rfloor$ best agents ('elite') to imitate which is implemented by picking a random value u from a uniform distribution and making the entrant pick the strategy of the agent with index $\pi^{-1}(u \cdot \lfloor \epsilon \cdot |A_t| \rfloor)$.

We see that capital stock can hence be easily used to introduce the selection/ propagation and imitation factor for our Neo-Schumpeterian framework. In the next section, we will see how this capital stock comes about and introduce the remaining factor of deselection of strategies.

5.6 Capital stock and exit

Before formulating exit operationally, we want to know what makes firms exit and what function it has within an evolutionary process, in general, and our Neo-Schumpeterian model, in particular. In real-world economic situations, there are various reasons for a firm to exit a particular industry. A firm can decide to exit because it has achieved its goals, or to concentrate on core competencies and rolling back particular diversifications done in the past. More often, a firm is forced to exit because it runs out of financial means and is to be dissolved.

In an evolutionary framework, exit constitutes deselection of inferior specimens that in turn prevents further propagation of inferior mutations. Despite the fact that entrants imitate superiorly performing agents (and thereby do not propagate strategies of inferiorly performing agents), the entry mechanism would be hampered by a clogging up of the system with badly performing agents, as they would still affect the Herfindahl index and occupy market slots. We need exit both to comply with the principles of the evolutionary framework as well as to assure proper functioning of our Neo-Schumpeterian model.

In line with the most common reason to exit, bankruptcy, we decided to use the capital stock of agents to force them to exit if required. The argumentation is similar to the one used for ranking agents, the net capital stock level relates to the performance of an agent due to its strategy (in terms of average difference of production returns and R&D costs). So, by having agents exit that go bankrupt, we deselect inferior strategies.

The development of the capital stock is typified by a simple equation. The capital stock of agent i at the start of period $t+1$ consists of the capital stock at t, i.e. Q_{it}, adjusted for interest, minus costs of R&D (here: fixed costs C) during period t, plus the payoff $R^P_{i(t+1)}$ (as defined in subsection 5.4.2) at the start of period $t+1$:

$$Q_{i(t+1)} = R^P_{i(t+1)} - C + (1+r)Q_{it} \tag{5.16}$$

This expression for Q makes insightful what the economic allocation problem actually is: a struggle to have R exceed the periodic fixed costs C structurally. R&D yields technology to bring to the market, while marketed technology yields payoff. If $Q_{it} < 0$, then agent i goes bankrupt and is removed from the population, hereby discontinuing all of its projects and removing its technologies from the market. Since each agent starts off with Q^0, there a short period in which the agent must achieve a state in which payoff exceeds the fixed costs. We see that this principle of bankruptcy embodies the Evolutionary Economic deselection mechanism as structurally unprofitable strategies, i.e. those that (structurally) generate too little income (R) in comparison to the fixed costs (C) will make the agent go bankrupt and thereby deselect the strategy from the population. If D/C becomes lower, either by decreasing D or increasing C, it becomes harder to recover the fixed costs and the level of competition increases.

We have decided to introduce an intrinsic and exogenously given capital stock growth rate r which allows us to manipulate the development of capital stock and thereby influence the industry development. If $r > 0$, the agent gains a fraction r of capital stock per period. This can represent increase due to investment in alternative ventures or deposits. If $-1 < r < 0$, the agent looses a fraction $-r$ of capital stock per period. This can reflect levy of taxes, capital stock depreciation or devaluation. In the earlier case, we would do agents with a high level of capital stock a favor. In the latter case, we put a ceiling effect on the development of capital stock and thereby limit the lead early entrants have over late entrants, thereby introducing a more fair competition. This way we can use r to manipulate the strength of deselection forces and through the changes in market concentration thus invoked also entry of imitations.

5.7 Measures and operationalization

We now have operationally defined the largest part our conceptual TCE model, we however yet have to operationalize collaboration propensity! The great advantage of using simulation is that one has great control over what data to collect. Here, we selected the most straightforward method and measure collaboration propensity on the output side by registering the absolute number of collaborative (solo) projects Γ^D (Γ^S) being finished and determining relative preference for collaboration over working solo in terms of the fraction $\Gamma^D/\{\Gamma^D + \Gamma^S\}$ of projects conducted in collaboration. From here on forward, we will use the short-hand notation $\Lambda := \Gamma^D/\{\Gamma^D + \Gamma^S\}$ to refer to the *fraction* of projects in which agents collaborate.
We will now evaluate the relationship of each independent factor in the TCE framework (complexity, complementarity, appropriability and competition) with the collaboration propensity and formulate the operational level hypotheses.

Although we have signaled some shortcomings of the operationalization of *complexity* in 5.2 (a.o. lack of the dimension 'specificity / maturity' of knowledge and lack of the dimension 'non-decomposability' of technology), the dimension of intricacy of relationships of elements is very prominent in the form of K (and in fact also one of the features of the NK landscape for which we have adopted it as technology landscape), so we will actually be testing whether meeting only this dimension closely is sufficient to explain the hypothesized effect on collaboration propensity. So, our hypothesis states that an increase in complexity renders more projects being conducted in collaboration, which is operationally defined as:

$$K \xrightarrow{+} \Lambda \tag{5.17}$$

In subsection 5.2.4, we however also noted that at least one of the properties of technology that we have discerned at the outset in section 1.3, namely non-decomposability, is unaccounted for in the NK technology landscape. We rather observe a tendency to the opposite, in the form of a regression to the mean also known as the complexity catastrophe phenomenon. So, apart from the possible emerging urge to collaborate upon increasing complexity K, we do expect K to somehow also dim this urge.

In subsection 5.2.2 on the operationalization of collaborative innovation, we have seen that the sector-level factor of *complementarity* strongly relates to -what we have called in the TCE framework- the 'scope of control' or 'set of competencies' which we have operationalized as breadth of expertise E. Recall that the breadth of expertise E is the same for all agents i.e. $|E_i| = |E_j| = E$ for all i and j. We argued that complementarity first rises in E until it reaches about $N/2$ as additional expertise would gradually lift the poor innovation performance (even of two collaborating agents). As of $E \approx N/2$, complementarity starts to drop in increasing breadth of expertise E as the marginal innovation performance increase drops due to relatively decent performance of the individual agent and the increasing overlap ($|E_i \bigcap E_j|/N$ increases in probability) and the decreasing complement ($|E_j \setminus E_i|/N$ decreases in probability).
From this we directly derive the somewhat esoteric expression $1 - |1 - 2E/N|$ expresses the degree of complementarity between agents at sector level. Following the TCE model, we expect that if $1 - |1 - 2E/N|$ increases that the collaboration propensity increases. We have decided to present this in a more common form by saying that collaboration propensity has a parabolic relationship with breadth of expertise:

$$E \xrightarrow{\cap} \Lambda \tag{5.18}$$

So, we expect collaboration propensity to first rise with scope of control, to reach a peak somewhere and thereafter start to drop.
Recall that scope of control and hence breadth of expertise concerns only one dimension of complementarity. In our exposition of the TCE model, we showed that technological interdependency (as an important dimension of complexity) also relates to complementarity. Through technological interdependencies, there are interferences that keep agents with limited scope of control locked into particular technological solutions. Additional expertise might not only improve particular complementary components but also help agents to overcome particular solution to which they were confined previously. So, in addition, we argue that complementarity increases with the number of technological interdependencies K. So, we do expect the relationship (at operational level) between expertise E and collaboration propensity Λ to be amped up by complexity K. A word of warning: as we have signaled before, the fitness of optima drops in K, so we have to aware that the 'amping up' of the emerging collaboration propensity for different levels of E might be hampered by the complexity catastrophe.

In the exposition of the TCE model in section 2.3 we saw that the collaboration propensity strongly relates to the level of spillover and the extent to which an agent is able to appropriate the returns from R&D effort. It was argued that the collaboration propensity increases if appropriability increases. Higher levels of appropriability would indicate less outflux of technological knowledge or less opportunities for the receiving party to put the outgoing spillover or even externality to own use at the expense of the original producer of the technological knowledge. In subsection 5.4.2 we saw that, due to our choice to operationalize technology as an 'instance' of a technological object (comprising techniques to produce, sell and service it, et cetera), we could readily introduce an operational mean to appropriate in the form of a 'patent' of that technology instance and its h-

Hamming-neighborhood. We then opted to operationalize appropriability as the running time ω of such a 'patent'. In line with the relationship in the TCE model, we expect:

$$\omega \xrightarrow{+} \Lambda \tag{5.19}$$

In subsection 5.4.3, we however argued that the operationalization of spillover, which is directly emanating from our 'instance' conception of technology, has some serious shortcomings. Apart from the implementation and simulation issues, we argued there simply is relatively little spillover (the number of technologies exchanged is a mere fraction of the grand total of 2^N)! So, direct spillover from collaboration hardly is a disincentive to collaborate! We however also saw that appropriability does tackle negative effects of externalities. Our theoretic framework does not allow predictions concerning externalities, so, we are not just curious to what extent appropriability affects collaboration propensity and hence the level to which the 'non-adherent' spillover still is a significant disincentive to collaborate, but also the effect on the collaboration propensity in the presence of externalities.

In the TCE model, we argued that the fierceness of competition determines the extent to which the non-appropriable spillover determines the collaboration propensity. If competition is fierce, the consequences of non-appropriable spillover ending up being used by the collaborator or one of its affiliates against the originator are likely to be more detrimental. On the other hand, the complementary knowledge provided by competitors is argued to be ever more crucial in survival.
We now see that if there is little spillover (or at least little non-appropriable spillover), agents are eager to collaborate to withstand competition. If there is much non-appropriable spillover, agents are more reluctant to collaborate to prevent leaking competitively sensitive information.
As we have seen in section 5.4, we can use both demand size D and market tightness (or quality preference) ψ to tune the returns per technology and thereby operationalize the level of competition. From the capital stock equations formulated in section 5.6, we know that we can also use the level of interest r or even the fixed cost C to make it easier or harder for agents to recover the costs and thereby tune the level of competition. From subsection 5.5.1, we know that we can also use the entry intensity (and then especially h_0) to tune the average market concentration and thereby the number of agents striving for returns. So, we have several options to operationalize the level of competition. We have chosen for the most simple and common concept associated with the level of competition, demand size D, to formulate our operational hypothesis.
Presuming an ordinary level of spillover, we argued that if the competition increases in terms of less credits D to share, agents are less likely to collaborate, or alternatively, if there are more credits being disbursed, agents are less concerned with sharing these credits:

$$D \xrightarrow{+} \Lambda \tag{5.20}$$

An attentive reader should have noticed that we expect that the current operational model does *not* feature considerable levels of spillover. If there is little spillover, there of course is little non-appropriable spillover and hence we expect the collaboration propensity to be *relatively insensitive* for changes in market demand size! As we however are able to tune the level of externalities and we already noted that means to appropriate are effective in protecting from (opportunistic) use of those externalities, we are curious what the effect is of level of competition on the relationship of externalities ρ and collaboration propensity Λ.

In the subsequent chapter we will run simulations, controlling each of the TCE factor operationalizations K, E, ω and D and measuring the collaboration propensity Λ.

Chapter 6

Simulation results and statistical analysis

In answering our research question about the effect of complexity on collaboration propensity, we have established an adorned TCE model in section 2.3. We have operationalized this TCE model into the Neo-Schumpeterian model presented in chapter 5. We have then translated the direct causal relationships of the TCE factors (being disaggregations of the uncertainty dimensions) with the governance form as formulated in subsection 2.3.2 within the realm and terminology of that Neo-Schumpeterian model into the operational hypotheses as formulated in 5.7. In this chapter, we will investigate each of those hypotheses by running simulations for various values of the independent variables (technological complexity by means of interconnectivity K, complementarity by means of level of expertise E, appropriability by means of patent duration ω, the level of competition by means of demand size D) and register the effect on the independent variable (collaboration propensity by means of the fraction of R&D projects that is conducted in collaboration Λ). As discussed, we inspect the effect of K in conjunction with one of the other operationalizations on Λ. As complexity is the main factor we are interested in, we will also (in one go) inspect the interactions with each of the other TCE factors. In our description of the Neo-Schumpeterian model, we already hinted on shortcomings of our operationalizations in relation to their TCE counterpart. In anticipation of the actual analysis of data, we will briefly place remarks on the hypotheses and reason about the consequences for the viability thereof.

As we have seen, the operational model contains many more parameters for which we do not directly investigate the effects. In line with the methodology provided in chapter 4, we will hence have to describe and justify the selected values for those parameters, and we will do so in section 6.1.

In many papers concerning Neo-Schumpeterian models, authors usually simply describe the simulation results and engage in appreciate theorizing about the implications. Here, as described in section 6.2, we take a somewhat more formal approach and will, for each factor (and its interaction with complexity), establish a couple of fundamental mechanisms emanating from properties of (specific modules of) our operational model. We will not only describe the causes, but also formalize these in mathematical terms and contest our claims in a non-linear regression analysis. We will eventually briefly evaluate the findings in 6.6 and -in the end- infer on the qualities of our operational model and implications within the context of our TCE model in chapter 7.

6.1 Parameter settings

The behavior emerging in a Neo-Schumpeterian model is for a large part outcome of the input parameter settings. In chapter 4, we distinguished several types of parameters. We distinguished parameters that relate directly to the conceptual model, which are operationalizations of the conceptual factors. We will control those in order to answer our research questions. We also distinguished 'auxiliary' parameters that are there to complement the operational definition of the conceptual model, and 'technical' parameters that are required to come to an actual software implementation without direct conceptual counterpart.

In a Neo-Schumpeterian model, there often are too many parameters to fully explore the system behavior for, which is the case even for our model of limited size. We started with picking a set of reasonable values. We then followed the procedure of 'bootstrapping' proposed in chapter 4 to get a better set of auxiliary and technical parameters.

In this section, we will present the exact parameter values we have chosen (or ended up with) and justify for them. The remainder of this section is arranged as follows. We will first shortly discuss our choice for the range and granularity for the parameters that are our factor operationalizations. We will then look at the development of the market (and hence the technology frontier), the collaboration propensity and strategy (population) over time and select the simulation time horizon R from that. The collaboration propensity is strongly affected by the strategy that in turn develops under the influence of entry and exit. Exit is affected by the 'financial' auxiliary parameters C, Q^0 and r, which we will discuss next. In additional, the number of technologies that an agent is allowed to bring to the market strongly affects the exit intensity. As we will show, we will limit L, the number of technologies an agent can have on the market. There however is one stronger factor to drive the market pressure: the entry intensity. The entry intensity and -in the end- the number of agents on the market are controlled by the parameters in the model in equation 5.14. We will specify those entry intensity parameters as well. As there is little connection to empirical concepts such that these parameters, arguably, are technical parameters already. We will discuss several (other) technical parameters in the last paragraph of this section.

Eventually, we thus obtain the quantified, operational model that we will use to infer on the effects of the parameters K, E, ω and D which we already isolated as operationalization of TCE factors in section 5.7.

6.1.1 Specification of range and granularity for factor operationalizations

For the moment we will fix $N = 72$ as it primarily affects the variation in fitness values and therefore is believed to only shift particular figures rather than structurally changing behavior and outcomes. We will typically select a grid of -say- ten values per parameter across its whole range and only zoom in on particular subranges or change the granularity if figures suggest such is required (we will however see that such is not required as the variables behave well). We will typically look at $K = 5, 15, \ldots, 65$, $E = 10, 20, \ldots, 60$. Parameter ω will depend on the simulation time horizon R and as we will see, we will need to control also for the level of reverse engineering ρ for which we will typically pick $\rho = 0.00, 0.15, \ldots, 0.90$. We will discuss the values to pick for D later, as this is to be related to other 'financial' parameters.

6.1.2 Development over time

We will now first stipulate the development of the market (and technology frontier) and relate to that the development of the output parameters to come to a decision about how many periods we will run each simulation. In figure 6.1 we see a typical plot of the market over time, with on the horizontal axis the period in time, and on the vertical axis the global fitness of the technologies on the market. Each dot represents a technology and the color of each dot reflects the number of agents that bring that technology to the market. The dot is green if only one agent brings the technology to the market, the dot is red if the number of agents equals the maximum number for the whole simulation and the color of the dot otherwise reflects the number in between the minimum and the maximum. We see that the technology frontier (i.e. the technologies invented and brought to the market) gradually progresses, becomes more narrow and eventually the development levels off (here to a fitness level of about 0.77, meaning that the fittest technology on the market has a fitness value of 0.77).
As we see from the scattered green dots far below the technology frontier, agents that just enter bring inferior technologies to the market and only gradually replace them if they develop better technologies through invention and innovation.
We measure the collaboration propensity by registering the fraction of the projects that is conducted in collaboration and calculating the average fraction at the end. In figure 6.2 we see that the collaboration propensity (green) develops over time and that the average collaboration propensity

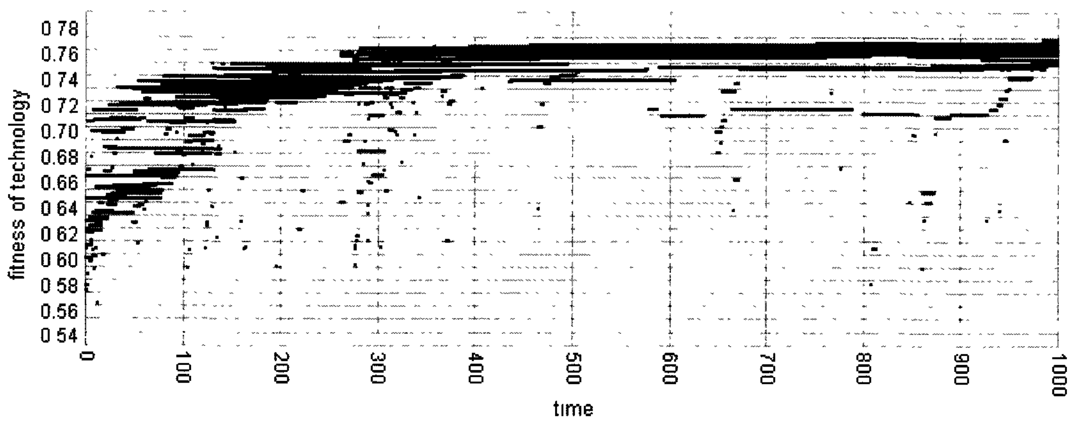


Figure 6.1: Technology frontier development over time. Each dot represents a fitness bin at a particular point in time. The color of the dot reflects the number of technologies on the market within that fitness bin.

is about 0.75. Here, we calculate the running average (the thick line) collaboration propensity as of period 700 to cut off the disturbances from onset behavior of the system.

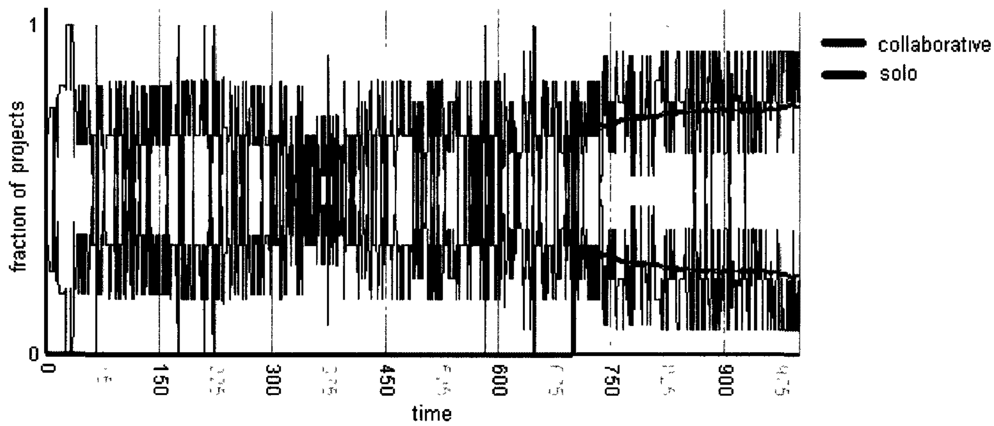


Figure 6.2: Development of the complementary propensities to collaborate (green) and to work solo (purple) over time. The thin lines plot the fractions of projects per period over time and the thick lines starting at $t = 700$ are the running averages thereof.

Trial simulations suggest that running each simulation for $R = 1000$ periods would leave sufficient opportunities for the strategy parameters to develop and that increasing the running time would seriously slow down the generation of data without remarkable changes in output.
Only during data-analysis, we realized that not only the behavior that emerges at the time of a developed technology frontier is interesting, but also the behavior that is apparent at the time the technology frontier is still developing. So, we have decided to also include investigating the propensity at period in time $R = 200$ (and then calculate the average collaboration propensity as of period 100).

Be aware that we cannot just associate the situation at $R = 200$ with the state of a sector with a prematurely developed technology frontier or with the state of a premature sector. Let us briefly describe the situation of the sector we model in this *onset phase* ($R = 200$) and this *mature phase* ($R = 1000$).
Let us compare the properties of the premature sector with the properties of the sector in the onset phase of our simulation. In a premature sector, there are plenty of technological opportunities but

also a considerable level of technological uncertainty. So, although there is considerable uncertainty about the innovation strategy, there however does not need to be (and there likely actually is also no) uncertainty about the collaboration strategy. However, *in our case*, it actually is the population of collaboration strategies that is evolutionary conditioned during this onset phase. So, regretfully, we do not just see the evolutionary 'ideal' (but still myopic and boundedly rational) collaboration strategy when agents are facing a premature technology frontier, the collaboration strategy population still is 'polluted' with inferior strategies. We hence have to bear in mind that our results are still distorted due to the insufficiently evolutionary conditioned strategy parameters. We however do argue that the state of the sector in the mature phase does closely resemble the properties of a mature sector. Apart from the fact that the technology frontier has progressed and that the technological opportunities are low, the collaboration strategy has been subjected to considerable evolutionary forces due to the many exits and entries. Due to this, the population of collaboration strategies is no longer polluted with inferior strategies, but the strategies are as good as completely conditioned to the situation of poor technological opportunities and progressed technological frontier.

6.1.3 Costs and payoff parameters

The market conditions are made a forceful driver behind entry and exit, such that pivotal parameters are sufficiently evolutionary trained. There actually are four parameters that can be used to achieve that. At the moment, agents pay a fixed periodic price of $C = 10$ to finance its R&D. On the other hand, when agents enter, the initial capital stock is only a mere $Q^0 = 80$. So, agents that are not able to get sufficient returns (i.e. less than C) from R&D within a couple of periods will be forced to exit. If Q^0 is (too) high, there is a certainly higher probability that the agent will hit a (top-)fit technology, regardless of strategy. To filter such cases and to limit the variance in final results obtained, we have decided to severely limit Q^0.
Apart from the fact that agents are required to quickly enter the market with sufficiently fit technology, there also is a *continuously* present urge to perform. The market periodically disburses $D = 200$ credits (the so-called demand size). Thus, with equal market share (and no capital devaluation), at most 20 agents will be able to cover their periodic R&D costs.

6.1.4 Market limitations

We furthermore limit the number of technologies L a single agent can have on the market to two, typically its two (Simonian) fittest technologies yet brought to the market. So, for an agent to survive, these two technologies should yield more than C, structurally. It has been decided to limit the number of technologies L because the industry otherwise often tipped to a situation as depicted in figure 6.3c in which a single agent dominates the industry by simply having many technologies on the market and thus receiving the lion-share of the disbursed credits.

The market is furthermore limited to allow $M = 30$ technologies. If the market capacity M is large and especially larger than L times the inflection point of the entry probability curve (i.e. $M \gg L * h_0$, see equation 5.14), agents can effectively and collectively protect their individual interests by working solo, as they are then less of a threat to the income of one another. A prerequisite for this to hold is of course that the total demand size is large enough for each agent to cover the fixed costs of its payoff. To understand this, we have to realize that if M is large, the probability of technology being pushed off the market is very small, since for that to happen $A * L$ should be bigger than M (and due to the presumption of $M \gg L * h_0$, this is very unlikely). So, no matter what the fitness is of the technologies being marketed, agents are able to reap credits of their technologies. If they furthermore collaborate, the collaborating parties are likely to have to share these credits (i.e. if it is sufficiently fit and thus among each agent its top L technologies). It must be said that

we largely overcome this by setting the market tightness ψ such that inferior technologies do not generate enough payoff to cover the fixed costs.
Unless the market is extremely tight (ψ large) or there are (strong) positive scale advantages ($\xi > 0$), sharing (even of a top-fit technology) will -in general- yield less payoff than reaping benefit of a mediocre technology. Obviously, collaboration is unlikely to survive as a strategy under such conditions and, indeed, we end up in a situation in which agents collectively protect their interest by collectively working solo.
So, to stimulate agents to obtain fit technology, we will generally pick M close $L * h_0$ and ψ relatively high. As the probability is higher that inferior technologies are pushed off the market and strategies that are more likely to yield superior technologies are more likely to survive. Here we set $L = 2$, i.e. each agent can have two alternative technologies on the market. We furthermore set $\psi = 5$, i.e. there is a clear preference for quality, especially if the technology frontier is broad. We already mentioned that $\xi = -1$, i.e. agents equally share the payoff and there is no scale (dis)advantage whatsoever.

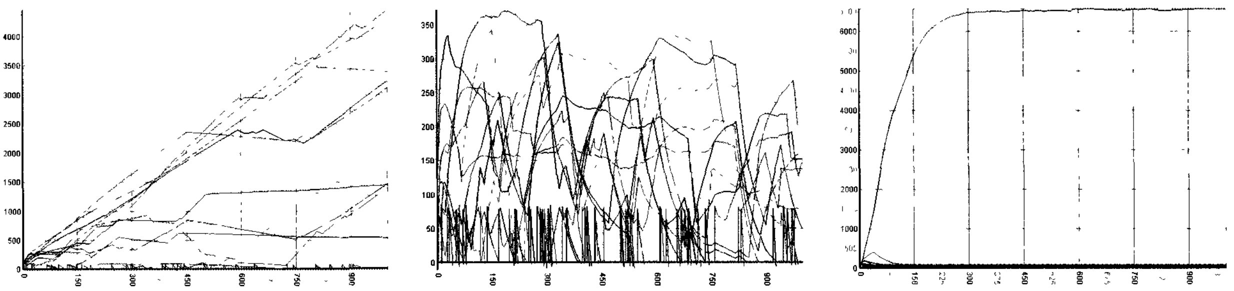
6.1.5 Fine-tuning capital stock development given the market limitations

If there is no capital devaluation, i.e. $r = 0$, agents accumulate capital to high levels, making the industry as a whole relatively insensitive for new entrants. A positive difference in capital of one over the other agent means the richer agent is able to conduct more R&D projects before being forced to exit the industry. As the richer agent is able to conduct more R&D, it is more able to (re)consolidate its position upon market shocks than is the poorer agent. In long-term perspective, a financial advantage is to be seen as relative power to diminish the poorer agent its income below the structurally required C level (to even push the other agent off the market). Thus, financial advantages are self-reinforcing through the ability to recover from market shocks and (re)consolidate the position. As you can see in figure 6.3a some agents indeed seize power and are able to consolidate it.
An easy and effective way to ameliorate evolutionary forces is to prevent capital accumulation to levels that make particular agents nearly invulnerable. This can be done by introducing devaluation of capital by setting the interest r below zero. After some tuning, we have decided to have each agent loose 5 percent of its capital stock per period. In the operational model, this is encoded as $r^+ = 0.95$, which boils down to $r = -0.05$. If you compare figure 6.3b with figure 6.3a you indeed see more dynamics in the population composition. It is expected that this also improves the development of the pivotal strategy parameters.

As far as the parameter settings for entry intensity are concerned, we have to take care that there are enough agents to fire up competition, i.e. that the point of inflection h_0 is sufficiently high. We take $h_0 = 12$. It is furthermore important that the system does not suffer shocks of heaps of agents entering (and thereby exiting) as this instability will hamper development of the strategy parameters. We select the horizontal scale $\gamma = 0.80$ such that the entry intensity only gradually increases with an increase in market concentration. We furthermore want a near instant reaction to changes in concentration, such that agents present do not enjoy a low concentration for too long a time. We hence have a high frequency at which entry is evaluated by the system, say $p = 2$.

6.1.6 Technical parameters

We have only a small number of so-called 'technical' parameters. The elite fraction $\epsilon = 0.2$, such that the top 20% of the agents is imitated. Making $\epsilon = 0$ would stifle further propagation of the strategy of a good second agent, for instance. Making ϵ large would hamper convergence of strategy parameters as the strategy is near randomly selected from the pool rather than selecting one that is performing well.



(a) Without devaluation, $r = 0$ ($r^+ = 1.00$) and $L = 2$

(b) With five percent devaluation, $r = -0.05$ ($r^+ = 0.95$) and $L = 2$

(c) With five percent devaluation, $r = -0.05$ ($r^+ = 0.95$) and $L = 20$

Figure 6.3: Development of capital stock of the agents over time for different levels of devaluation r and number of technologies L an agent is able to market. The horizontal axis represents time (in number of periods), the vertical axis represents the capital stock (in number of credits). Each separate line represents the capital stock of a distinct agent over time. Colors are used to be able to distinguish lines from one another.

We currently set the patent neighborhood size $h = 5$. If we would make h very large, then many technologies would end up infringing that patent, thereby providing great market power to the agent owning that patent and hampering evolution of the strategy population. Especially if we introduce reverse engineering, the h should not be too large. If we make h too small, the probability of a patent being infringed is very small (recall that there are 2^N different technologies!). We furthermore fix the patent owner share to $\upsilon = 0.80$, such that the owner will always (at least) receive 80% of the payoff. Too high a value would harm the benefits of spillover and/or externalities (as licensees hardly benefit), while too low a value would deteriorate the function of a patent (as there still is insufficient appropriation).
The 'history weight parameter' s in equation 5.5.2 for determining a rank for agents (for imitation), we already fixed $s = 0$ and did not even expose this parameter in the graphical interface. Another technical variable that is not exposed in the graphical interface is the 'error' in imitation of the strategy parameter δ. In trial simulations, we have tried different settings, but $U[-0.1; 0.1]$ seemed to work just fine, so we left it as is.

Let us now look at the results of simulations in which we do a two-dimensional survey of effects of (TCE) factors on collaboration propensity.

6.2 Data-analysis methods

In this section, we will briefly discuss how we generate data with our simulation model, the format of the data obtained, how it will be presented in this essay and the exact methods we use to analyze that data (and an explanation why we do it that way).

Firstly, as prescribed in section 4.5 on data-analysis, we start off with parameter settings that define the values for the auxiliary and technical parameters. We will use the parameter settings just described in section 6.1 to quantify the software implementation of the operational model described in chapter 5. We will then decide which of the hypotheses formulated in section 5.7 we will investigate and thereby obviously which independent variables we will need to fix and which independent variables we will need to experiment with.
The simulation application has us pick two independent variables and specify the array of values for each and the number of simulations per pair of values for which simulations will be run. We will hereby pick the values as agreed upon in subsection 6.1.1 on granularity and range of operational variables. Say we want to investigate the effect of E in conjunction with K, we then pick $E =$

$10, 20, \ldots, 60$ and $K = 5, 15, \ldots, 65$ adding up to $7 \times 6 = 42$ pairs of values. In general, we will run 15 simulations with different seed values for each pair of values, making the total number of simulation runs in our example $15 \times 42 = 630$.

Secondly, we then run the simulations for the list of values (scenarios) and for each simulation we log time-series data, e.g. for the number of agents in the system, the number of projects per type, the capital stock for each of the agents, et cetera. At the end of each simulation, we append a record to an SPSS data-file for further processing. These records typically have the form of $\{\ldots, p_1, \ldots, p_2, \ldots, \lambda \ldots\}$, where p_1 and p_2 are the variables controlled for in the simulation and λ is the time-averaged collaboration propensity for that single simulation run (as described in section 6.1).
In visually presenting the simulation results, we will plot the three-dimensional data $\{p_{1i}, p_{2i}, \lambda_i\}$ in an isometric two-dimensional representation, where $i = 1, \ldots, I$, with I the total number of scenarios (pairs of values). We thus get figures like figure 6.4a. In this example, the axis pointing to the bottom, left-hand side is the axis of the level of expertise E, the axis pointing to the bottom, right-hand side is the axis of the level of technological complexity K, and the axis pointing straight up is the axis of the collaboration propensity Λ. Each dot in the figure represent the average collaboration propensity during a single simulation run for a particular pair of input parameters (i.e. here a value for K and E). To ease visual inspection, each pair of values (for which we have 15 instances) has a distinct color. To give a sense of the development for variation in either one of the parameters, we calculate the mean collaboration propensity over these 15 simulation instances for each pair of values. We then draw a grid connecting each mean value point with its Manhattan neighbors to form the -what we call- 'mean grid'.
If necessary, we will also control mediating variables and auxiliary and technical variables. Here, we will at least conduct simulations for both the onset ($R = 200$) and mature phase ($R = 1000$) and investigate the difference in emerging behavior. As hinted in section 6.1.2, we expect differences due to the weak evolutionary selection regime and due to the fact that the technology frontier is still developing in the onset phase. We will also show that the results obtained are robust for the starting seed chosen, such that our conclusions gain internal validity. From the looks of the resources left for this research and writing of this essay, we will not be able to study the robustness of our simulation for technical variables or deepen our understanding of the interference of operational TCE factors.

Thirdly, the common practice to discuss the results from Neo-Schumpeterian simulations is visual inspection and providing a verbal account of what is observed in the graphical representation of the data. Surely, we will also start out with giving a verbal account of the phenomena depicted in the figures. We however noticed that in coming up with an explanation, we often were not sure about the exact underlying causes. In order to deepen our understanding, we were compelled to study the behavior of the simulation model in highly reduced form (in something we call a 'fundamental setting'). In doing so, several (conceptually rich) explanations we initially devised thereby perished. In order to convince the reader of the correctness of the explanations, we have chosen to write out our data in records to an SPSS data-file to infer statistically on the relationships of controlled variables and dependent variable. We have decided to establish a regression model composed of terms that reflect these 'fundamental causes' and to subsequently show that there indeed is an acceptable coefficient of determination R^2. So, rather than suggesting the causes without obligations to justify for the claims other than making it plausible, we have decided to provide strict regression models.

6.3 Complementarity and Complexity

Following the method described in section 6.2, we will here inspect the effect of the operationalization E of the factor complementarity of the TCE model in conjunction with the effect of the operationalization K of the factor technological complexity on the measure Λ for collaboration propensity. We will thereby adopt the parameter settings provided in 6.1 to quantify the operational

model provided.
We will now first briefly recapitulate the hypotheses as emanating from the TCE model, the operational counterpart and remarks on how shortcomings of our operational model might hamper the relationship. We will describe the obtained simulation data and give a verbal account of the phenomena observed. In line with our more formalized approach, we suggest underlying causes and provide mathematical terms for each of these fundamental causes to be included in our non-linear regression model. Eventually we will fit the regression model and evaluate the results. We will make plausible that the result obtained also are robust for the technology landscape chosen. Finally, we will evaluate the findings in the light of our reexamination of the operationalization of the relationship(s) in the TCE model.

6.3.1 Hypotheses

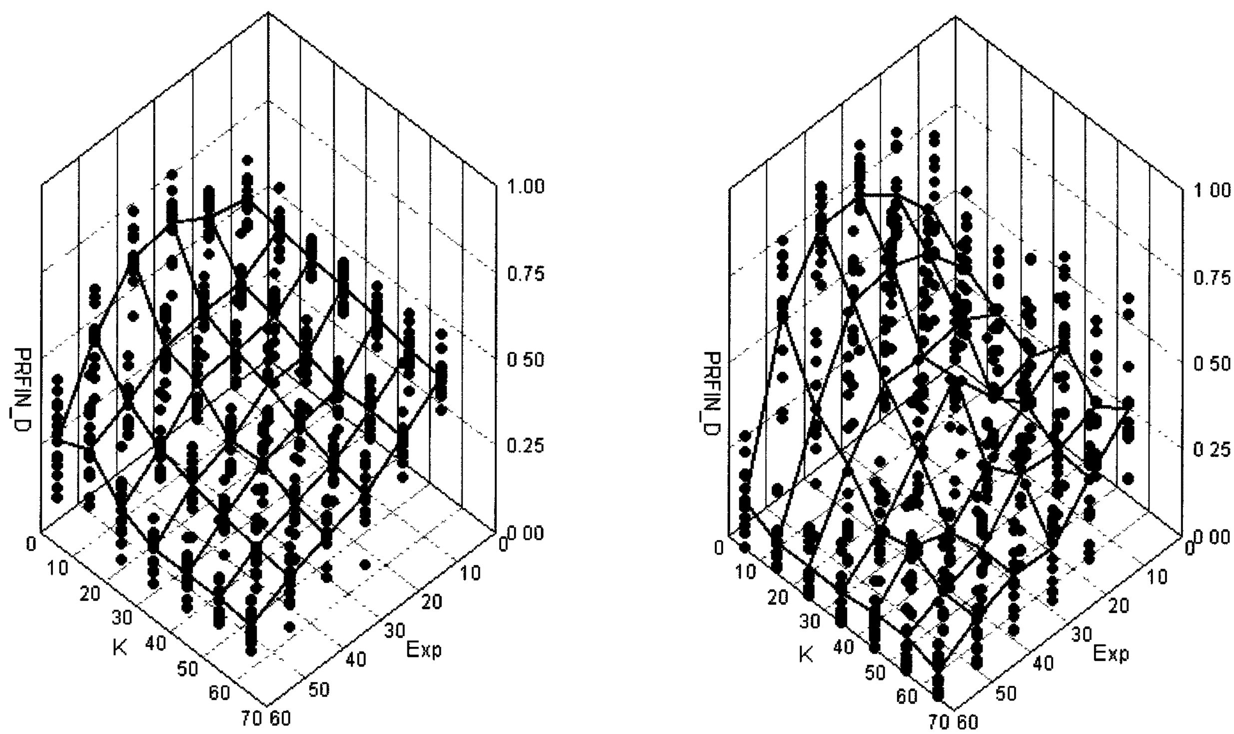
As said, we will inspect the effect of complexity in conjunction with complementarity on collaboration propensity .
As we know from subsection 2.3.1, the TCE model predicts that if complexity increases, ceteris paribus, that firms are inclined more to seek complementary knowledge both for operational and strategic reasons. Operational advantages are preemptively signal incompatibilities and achieving synergies by overcoming limitations to capabilities. Strategic advantages are overcoming high costs of outsourcing and internalization while maintaining flexibility and preventing lock-in and sunk costs. We argued that under high complexity, collaborating is both statically as well as dynamically efficient.
In formulating our operationalization of complexity in section 5.2, we signaled that the technology landscape we picked does facilitate immediate operationalization of the dimension intricacy (the number of technological interdependencies), but regretfully comes short in operationalization of the other dimensions. In section 5.7, we settled with the limitations of our operationalization and formulated the hypothesized relationship between complexity and collaboration propensity as $K \xrightarrow{+} \Lambda$, i.e. that the technological intricacy positively affects the fraction of projects that is collaborative.
In evaluation of the technology landscape, in subsection 5.2.4 we noted that especially the lack of operationalizations of the dimensions 'specificity/ maturation' and 'non-decomposability' might have serious consequences. Moreover, there is the phenomenon of complexity catastrophe that has us doubt about the strength and even sign of the relationship.

We also know from section 2.3.1 that the TCE model predicts that if complementarity in the sector increases, ceteris paribus, that firms also are inclined more to seek complementary knowledge to overcome the technological uncertainty. The operational advantages are the extension of capabilities (operational control over development of components) and the capability to redirect the R&D trajectory when signaling incompatibilities across the respective capability boundaries. These operational advantages hence increase both the efficiency as well as effectiveness of innovation. We also signaled in 5.2.4 that due to our limited conception of innovation and technology, our operationalization of complementarity is limited to the operational advantages and that the strategic advantages (learning and cross-fertilization of engineering knowledge) are not covered.
In section 5.7, we narrowed complementarity down to the dimension 'relative contribution to control' and argued that the breadth of expertise E is expected to have an inverted-U relationship with collaboration propensity. We hence came to the hypothesis $E \xrightarrow{\cap} \Lambda$.

Since we will have the opportunity to inspect the interaction between complexity and complementarity, let us shortly recap on that. In the evaluation of our TCE framework, we also discerned an interaction between complementarity and complexity caused by the dimension of the number technological interdependencies of complexity, K, on the one hand, and the number of technological interdependencies of the components contributed by the collaborator, on the other hand. In the operationalization of collaborative landscape search, we already noted that due to the random interconnection of elements (as a property of the NK landscape), that the interdependency of components by and large equals the interdependency of fields of expertise under control by the two agents. From this we expect the simple interaction that the complementarity effect is amplified by complexity. We expect a shift upward in the collaboration propensity, in general. Again, the phenomenon of complexity catastrophe might be interfering.

6.3.2 Verbal account of results and suggested underlying causes

We ran simulations for $K = 5, 15, \ldots, 65$ and $E = 10, 20, \ldots, 60$, and for 15 different seeds per pair of values, both for $R = 200$ and for $R = 1000$. The results are visually presented in figures 6.4a and 6.4b. We will now first give a brief verbal account of these results and then propose two underlying mechanisms explaining the collaboration propensity as found. Upon a first glance of these figures, without any inference whatsoever, the curvature of the 'mean grid' is exciting: the data does not seem to support the *central* hypothesis that collaboration propensity increases with an increase in technological complexity! Just as we expect, we however do discern a parabolic curvature in the mean grid for varying E, especially in the mature phase, at least for low to moderate K. As we will later see, there in fact is only a slight distortion of this parabolic curvature for low E and high K.



(a) Onset phase, $R = 200$

(b) Mature phase, $R = 1000$.

Figure 6.4: Collaboration propensity Λ for various values in the K - E plane for $\omega = 0$, $\rho = 0$, both for the onset and mature phases

The effect of complementarity in terms of breadth of expertise of agents in the onset phase (figure 6.4a) differs from that in case of the mature phase (figure 6.4b). We see that in case of the onset phase, an increase in expertise -on average- discourages collaboration but that there is a small bump near low levels of complexity. In case of the mature phase, this 'bump' seems to actually shape the figure for a large part, giving the surface a parabolic curvature. For high levels of complexity, we see that the surface is no longer parabolic, but seems to be distorted by relatively high values for

low breadth of expertise.
The effect of complexity is weaker in the onset phase than is in the mature phase. We see that in the latter case there is a strong decrease in collaboration propensity for an increase in complexity, especially for intermediate breadth of expertise. In case of the onset phase, the effect generally is rendered by the 'bump' described earlier, and that the overall effect of complexity is weakly negative on collaboration propensity.

We argue that there are two underlying mechanisms explaining the collaboration propensity as found. First of all, the effect of the contribution of expertise is hampered by the properties of the technology landscape -and in particular the complexity catastrophe-. This distorts (intuitive) rationale for collaboration. It must be said that there is a baseline level of collaboration that takes place not only to reap (synergistic) innovation performance augmentations but also plainly to replace complementary components at the start of an R&D project. Second of all, the properties of the matching heuristic (and in particular ill-appraisal of the actual proposed improvement to the starting technology) increases the probability to engage in collaboration.
We will now discuss both of these two mechanisms and relate them to the effect on collaboration propensity of changes in the factors K and E. We will formulate model terms for each of these mechanisms to later build a regression model from those terms. We will then use these two mechanisms to explain the properties of collaboration propensity visible in figures 6.4a and 6.4b, i.e. for the different development phases (being the onset and the mature phase). Then we will form a regression model, fit it and discuss the results.

The effect of the actual contribution in expertise superposed by the complexity catastrophe

The first mechanism is that of the actual contribution in expertise superposed by the complexity catastrophe. In our discussion of the hypotheses, we stated that the contribution of a collaborator and the complementarity increases with K, we however see that the complexity catastrophe[1] causes a decrease in the maximum achievable fitness (and thereby in the attractiveness of collaboration) and as such rather causes the opposite: a drop in collaboration propensity for an increase in K!
With an increase in complexity, the number of epistatic relationships increases and the variance in (global) fitness decreases while the mean remains 0.5. With an increase in K, the fitness of optima generally drops (see figures B.1 and B.2 in appendix B). Consequently, the 'maximum attainable fitness' is strongly affected by the complexity catastrophe. The (slight) improvement by involving a collaborator is *higher* if the complexity is *lower*! We thus argue there is a -counterintuitive- *decreasing* effectiveness of collaboration upon increasing complexity caused by the superposition of the 'maximum attainable fitness'! We see that the 'side-effect' of a change in complexity on the fitness of optima that is described in subsection 5.2.4 now manifests itself by affecting the 'attractiveness' of collaboration and leading to counter-intuitive emerging collaboration propensity. In that subsection, we also stressed that this regression to the mean fitness upon increasing complexity actually violates the property of technology that an increasing in complexity brings about an increase in non-decomposability. That non-decomposability would after all, make performance/ fitness outcomes regress to the *extremes* and also reduce the number of properly performing technologies drastically! Since we cannot justify for these contrasts and cannot think of real-world examples that actually display such properties, we are forced to conclude that we are looking at an artifact of the operational landscape search module. In subsection 7.3.1, we will elaborately discuss the shortcomings of this technology landscape search model.

We can also relate the fundamental findings (see appendix B) concerning the innovation performance augmentation (the fitness increase established by collaborating rather than working solo) to

1. We have introduced the complexity catastrophe in section 5.2.4. For more information, the reader is referred to appendix A or Kauffman (1993, p.52)

the fact that we also observe this parabolic curvature in E. This is strongly visible in figure 6.4b and to a moderate extent also in figure 6.4a. From these fundamental properties of collaborative search on an NK landscape, it is argued that the propensity to collaborate strongly relates to the contribution in fitness (of the collaborator) and that the increase in fitness and thereby the increase in payoff justifies collaborating and thereby sharing the payoff. In line with that, we conclude that if agents have a highly specific expertise (E low) or have a generic expertise (E high), the increase in fitness brought about by getting a collaborator involved is too insignificant to justify sharing payoff. We hence then see a low collaboration propensity.

The following term will be introduced in the final regression model to account for the decreasing effectiveness (in terms of fitness) of collaboration ($e^{\alpha_2(1-\bar{K})}$), which in turn is determined by the effectiveness (in terms of fitness) of complementarity ($\alpha(\alpha_0 - (\bar{E} - \alpha_1)^2)$) which has this distinct parabolic nature. We thus come to the following regression model term:

$$\Lambda \leftarrow \alpha(\alpha_0 - (\bar{E} - \alpha_1)^2)e^{\alpha_2(1-\bar{K})} \tag{6.1}$$

Hereby $\bar{K} := (5 + K)/10$ ($\bar{E} := E/10$) is a mapping of the range of values of K (E) onto $\{1, 2, \ldots\}$.

As mentioned, if agents collaborate, they enjoy an augmentation of the innovation performance by sharing control as well as better fitness assessment. If an agent starts with a fresh invention (rather than a reverse engineered technology) and works solo on improving that technology, this, however, not only limits its control or its fitness assessment qualities, it also has him stuck with the initial selection of complementary components. In reality, a firm selects particular complementary technologies that are standard or are sold by a supplier that is preferred for some reason in conjunction with improving matters within its own control. If an agent in our operational model now engages in collaboration, part of the complementary components of the invented technology that is outside its control will then be replaced with the (Simonian) top-fit technological components by the collaborator. This is likely to move the agent(s) to a different basin of attraction (with likely a fitter optimum). Collaboration then hence constitutes a 'concealed buying' of complementary components! So, a certain fraction of the collaboration propensity is likely to be induced by such 'concealed buying' on top of the fraction attributed to the increase in (synergistic) innovation capabilities.

The replacement of the components in the new invention with Simonian top-fit components is more likely to lead to globally fitter technology if the complexity is low. After all, in that case, there is little interference of complementary components upon blunt substitution as there are few technological interdependencies. Moreover, the Simonian fitness assessment is also a more accurate assessment of the global fitness, so the fitness assessments on which the collaboration decisions are based also better reflect the eventual joint performance. On the other hand, the synergistic innovation performance augmentation is really limited as the collaborator is hardly able to improve the components it just contributed and the principal agent does about the same improvements to the technology as it would do if it would work alone. So, it indeed appears as if the principal agent simply buys the complementary components from the collaborator and pays half the payoff for the final product!

If technology is more complex, there are more technological interdependencies and the initial substitution is less likely to yield immediate improvements, but there genuinely is synergy in innovation capabilities. So, we expect that collaboration to do 'concealed buying' of component technology for low levels of complexity is gradually replaced by collaboration to reap the synergistic innovation performance augmentations if complexity increases (but by that time the achievable innovation performance augmentation presses the collaboration propensity).

We argue that we cannot disentangle the effect of the superposition of the achievable innovation performance augmentation (which is decreasing due to the complexity catastrophe) and the just described 'concealed buying' of complementary components developing into the (suppressed) 'collaborating for synergy in innovation capabilities'. Adding an additional term for this 'concealed buying' mechanism to our regression model would simply yield interaction in coefficient estimations and thereby obscure our results without providing additional insights.

Ill-appraisal of amendment

The second mechanism is that of collaboration caused by ill-appraisal of the fitness of the proposed improvement to the starting technology.
The curve for $E = 10$ in figure 6.4b containing the measured collaboration propensity Λ differs from the curve for $E = 10$ in figure B.3 containing the measured increase in global fitness $\bar{D}_{KE}$ obtained when collaborating over working solo. We observe that the collaboration propensity Λ does not develop in line with what we expect from the development of $\bar{D}_{KE}$ if we change the breadth of expertise E. We see that, especially for $E = 10$, Λ is relatively high compared to $D_{KE.}$ and does not drop like the drop in difference $D_{KE.}$. So, there is relatively a lot of collaboration measured given the modest increase in fitness.
The reason for this discrepancy is sought in the variance of the Simonian fitness and the way the fitness value is used in the matching algorithm. This Simonian fitness increases if the breadth of expertise E decreases as the fitness $F(E,T)$ expressed in equation 5.2 is the mean of fewer elements. Recall that our matching heuristic makes the principal agent willing to collaborate with another agent if this potential collaborator his Simonian fitness contribution to the starting technology Δ_{ij} is high enough (see section 5.3). If the breadth of expertise is smaller, the variance of the Simonian fitness assessment is larger and hence the variance of the fitness contribution is larger. As the decision of working together or solo is conditioned on the fact that this difference in fitness must exceed a particular threshold (δ), the probability of working together increases with decreasing breadth of expertise! Let us refer to this effect as 'ill-appraisal' as due to a narrow fitness assessment scope, the eventually obtained fitness contribution after execution of the project in collaboration in comparison to the obtained fitness when the project would be conducted solo (i.e. what we call the innovation performance augmentation) is overvalued. For a detailed account of this ill-appraisal of amendments, see appendix C.
Although the matching algorithm is perhaps peculiar in that it is a top-down, highly simplified model of how agents form alliances, it is stressed that this ill-appraisal is not necessarily an artifact of this matching algorithm. It is also likely that highly specialized firms also poorly assess proposed adjustments, as they are unable to overlook all implications of these adjustments. Under the presumption that there is a(n) (initial) universal degree of preference for collaboration, more specialized firms are perhaps indeed more likely to agree in working together.

We come to the following -rather generic- term to introduce an increase in collaboration propensity due to ill-appraisal:

$$\Lambda \leftarrow \beta(\bar{E}^* - \bar{E})^{\beta_0}\bar{K}^{\beta_1} \tag{6.2}$$

Hereby $(\bar{E}^* - \bar{E})^{\beta_0}$ accounts for the decrease in appraising error if E increases (we demand that $\beta_0 > 0$), while multiplying with the term $\bar{K}^{\beta_1}$ also allows for some interaction with the level of complexity as we believe to observe a slight distortion for high levels of K. Note that we define $\bar{E}^* = 1 + \max \bar{E} = 1 + 6 = 7$ ($\bar{K}^* = 1 + \max \bar{K} = 1 + 7 = 8$).

6.3.3 Fitting the regression model

We see that in the onset phase (figure 6.4a), the collaboration propensity is actually predominantly decreasing in the level of expertise. Since the technology frontier is not well progressed, it is relatively 'easy' to invent and develop a technology that is eligible to enter the market. The frontier has not yet reached the limits superposed by the complexity catastrophe and as collaboration has a higher probability of producing relatively fit technology eligible to enter, collaboration effectively

increases the probability to survive. Although the contribution of a collaborator is relatively moderate for limited breadth of expertise, the inclination to collaborate induced by 'ill-appraisal' is not being 'punished' as agents still obtain sufficiently fit technology.
In the mature phase (figure 6.4b), the technology frontier is close to the 'maximum attainable' determined by the joint effect of the complexity catastrophe and the complementarity benefit effect. The 'ill-appraisal' for low breadth of expertise E is generally weeded out (i.e. agents surviving have a high δ) since collaboration yields too little advantage in terms in fitness to justify sharing the payoff. The emerging collaboration propensity generally reflects the actual benefit in terms of additional fitness achieved by of collaborating. In case K is high, the development of the technology frontier takes (very) long, so we observe some remaining 'ill-appraisal' effects in the upper, right-hand side corner in figure 6.4b.
So, in the onset phase, the 'ill-appraisal' mechanism predominantly determines the emerging collaboration propensity, while in the mature phase, the 'maximum achievable fitness' predominantly determines the emerging collaboration propensity.

We come to the following regression model:

$$\Lambda \leftarrow \alpha(\alpha_0 - (\bar{E} - \alpha_1)^2)e^{\alpha_2(1-\bar{K})} + \beta(\bar{E}^* - \bar{E})^{\beta_0}\bar{K}^{\beta_1} + \epsilon \tag{6.3}$$

We obtained the coefficient estimates presented in table 6.1, with between brackets the t-value (coefficient estimate divided by standard deviation of the estimate).

	$R = 200$	$R = 1000$
α	0.0221 (7.80)	0.0770 (11.20)
α_0	12.841 (3.05)	10.002 (7.64)
α_1	3.600 (2.91)	3.232 (15.81)
α_2	0.583 (9.56)	0.321 (6.76)
β	0.179 (5.013)	0.00170 (0.43)
β_0	0.523 (14.75)	2.379 (2.70)
β_1	0.000 (0.000)	0.512 (1.01)
R^2	0.703	0.625

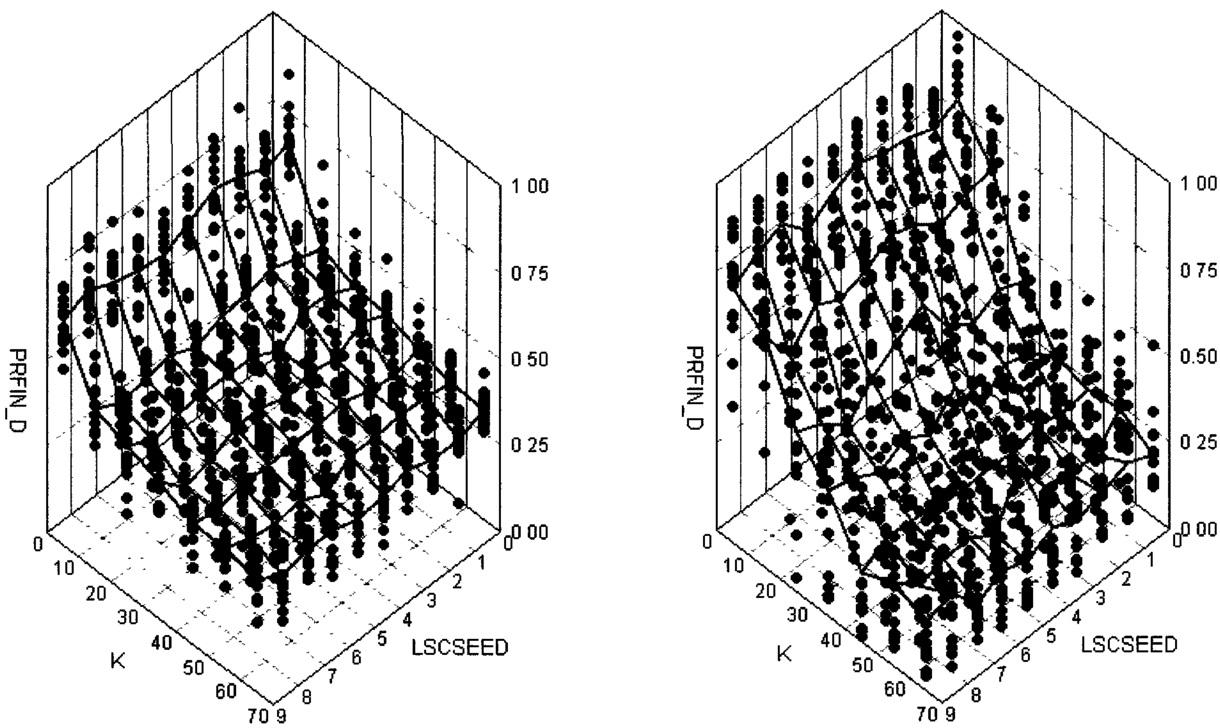
Table 6.1: Model coefficients with their t-value (coefficient divided by standard error) and R^2_{adj} for K versus E

From the fact that β is high (and its t-value is high) in the onset phase, we conclude that the ill-appraisal effect is present and has a significant effect in the results. With a progression of time and evolution of the sector into the mature phase, we end up with a β that has a low coefficient value and is relatively insignificant (low t-value). We conclude that the ill-appraisal effect is not strongly present any longer. From the development of β_0, we see that the role of the breadth of expertise in the ill-appraisal term develops from a steadily declining, but strongly present, to a steeply declining, moderately strong present over time. We indeed expect the ill-appraisal effect to be weeded out and this is a sign of that happening. Another salient detail is that β_1 (and hence interaction of ill-appraisal with the level of complexity) develops from being as good as absent in the onset phase, toward being modestly present in the mature phase. This is in line with our observation of the distortions for large K; the 'weeding out' of the ill-appraisal effect is weakest on landscapes with the combination of high levels of K and low levels of E.
From the t-values of α, we see that the innovation performance augmentation ('actual eventually obtained fitness contribution') term is highly significant, especially in the mature phase. Not surprisingly, the real benefit in terms of additional payoff reflects in survival rates of particular strategies. From the development of α_0 and α_1, we see that over time, the actual effect of complementary (i.e. the inverted-U shape) becomes more significant in the data, which we can also visually confirm. The drop in α_2 signifies the emergence of this innovation performance augmentation when the manifestation of the ill-appraisal effect as a rather constant collaboration propensity over various levels

of K is 'weeded out' over time. The ill-appraisal effect is independent of the level of complexity K, while this innovation performance augmentation shows a rather steep drop in complexity. This drop is caused by the manifestation of the complexity catastrophe that squeezes the difference in the fitness of the optima obtained and hence the magnitude of the performance augmentation (see appendix B).

6.3.4 Robustness for landscape seed

We see in figure 6.5a and figure 6.5b that the results appear to be robust for changes in the landscape seed for the case that the expertise breadth with the largest range $E = 40$.



(a) $R = 200$ (b) $R = 1000$

Figure 6.5: Collaboration propensity Λ for various values of K and different landscape seeds for $E = 40$, $\omega = 0$ and $\rho = 0$

If we now find support for robustness for this expertise breadth, we reckon that robustness also holds for other expertise breadth values. Note that we should not test these results against the filled out regression model for this expertise breadth, as that model also takes into account the other expertise levels and might thus be a relatively bad predictor. We rather cross-compare the distributions obtained for the different landscape seed. As we do not want to make assumptions about the underlying distributions, we resort to the non-parametric Kolmogorov-Smirnov and the Mann-Whitney test. We have to check all 45 possible pairs $(\{0,1\}, \{0,2\}, \ldots, \{0,9\}, \{1,2\}, \ldots, \{1,9\}, \ldots, \{8,9\})$.
The results for the onset phase indicate that there is only one case $(\{8,9\})$ in which we have to reject the null hypothesis that the distributions are equal (with an asymptotic significance of the K-S statistics of 0.044) and that the medians are equal (with an asymptotic significance of the M-W statistic of 0.037).
For the mature phase we obtain similar results. Only in the case $\{3,4\}$ the distributions differ significantly (asymptotic significance of K-S statistic is 0.044), but in this case there is no significant difference in medians detected (asymptotic significance of M-W statistic is 0.110).

Based on these findings it is concluded that the simulation outcomes for the current parameter-settings over the K - E surface are robust for changes in the landscape seed.

6.3.5 Evaluation

Our (supposedly robust) simulation results indicate that, in our technology landscape search model, technological intricacy insufficiently accounts for collaboration propensity. Ordinarily, collaboration means an expansion of innovation capabilities and improvement of fitness assessments, often allowing agents to move into a basin of attraction of a better optimum, especially if technological intricacy is high. In our technology landscape search model, however, a rise in intricacy causes a drop in the maximum attainable fitness, a drop in the increase in innovation performance ordinarily established by collaborating over working solo, and thereby a drop in the attractiveness of collaboration. We also saw that collaboration propensity is partially motivated by 'concealed buying' of complementary components if intricacy is low and (synergistic) innovation performance augmentation if intricacy is high. We however argued that this cannot be disentangled from the baseline collaboration propensity determined by the maximum attainable fitness (increase) subject to the complexity catastrophe.

We have seen in our simulation results, especially in the mature phase when polluting collaboration strategies have been weeded out (and, also, strategies are more attuned to the techno-economic conditions of the progressed technology frontier), that this complexity catastrophe indeed seems to superpose any positive effect of collaboration. Even for levels of expertise when collaboration yields the biggest benefits, i.e. when the contribution to control is largest ($E \sim N/2$), the gains in innovation performance stemming from collaboration are superposed by this complexity catastrophe. So, we find evidence for $K \xrightarrow{-} \Lambda$ and fail to find evidence for the presupposed shift upward in collaboration propensity upon an increase in K. The complexity catastrophe completely superposes the presupposed effect of the benefit of seeking complementarity knowledge on collaboration propensity.

Fixing the level of intricacy, we however do find evidence for the inverted-U relationship between the level of expertise and the collaboration propensity, i.e. $E \xrightarrow{\cap} \Lambda$. This is in line with expectations.

We also discovered an effect that was unanticipated in the theory which we have called ill-appraisal of the amendment to the technology starting point of an R&D project. As the valuation of the project has more variance, the probability of exceeding the yardstick for collaboration increases. This predominantly occurs in the onset phase, primarily due to the fact that the strategy population is insufficiently conditioned to the maximum attainable fitness as the technological opportunities are still plentiful. If the simulation runs longer, the strategies that collaborate more than justifiable from the increase in innovation performance are weeded out. Thereby the ill-appraisal effect vanishes from the population.

6.4 Appropriability and Complexity

Again following the method described in section 6.2, we will study the effect of the operationalization ω of the factor appropriability of the TCE model in conjunction with the effect of the operationalization K of the factor technological complexity on the measure Λ of collaboration propensity.

We will first recap on the hypothesis and the interaction of appropriability and complexity, hereby taking into account the remarks on our operationalization as far as they may distort this relationship. The TCE framework predicts that collaboration propensity increases with appropriability, but -as hinted already in 5.4.3- spillover is insignificant in our model. This is expected to nullify the effect of appropriability of collaboration propensity. However, we also noted that our model does contain the possibility to tune the level of externalities and that appropriability of course will affect the relationship of externalities with collaboration propensity. We will describe our findings on the role of appropriability sec, without externalities, only to immediately turn to analysis of the role of appropriability, where we control for the level of reverse engineering. We will then fathom the underlying fundamental causes for this latter case, then devise a non-linear regression model and show that we explain a considerable level of variance. We will make plausible that the results obtained also are robust for the technology landscape chosen. Finally, we will evaluate the findings in the light of our expectations.

6.4.1 Hypothesis

As explicated in subsection 2.3.1, the TCE framework predicts that if appropriability increases, the detrimental effects of spillover become less, the risk of opportunism decreases and hence firms are less reluctant to seek complementary knowledge through collaboration. Appropriability also guards against misuse of externalities and thereby restores the incentive to conduct R&D.
In subsection 5.4.2, we have introduced the operational means to appropriate the returns of the efforts done (to produce particular technology) in the form of 'patents' that protect the Hamming neighborhood of the technology string being produced and marketed. In line with this operationalization, we formulated the TCE model relationship of appropriability with collaboration propensity in section 5.7 as $\omega \xrightarrow{+} \Lambda$.
In subsection 5.4.3, we however argued that direct spillover of technology instances is expected to have little effect. We argued that this is caused by the extremely small chance of hitting a previously evaluated technology, but also absence of costs of assessing the fitness[2] and that hence transfer of technologies does not bring about a financial advantage. We furthermore argued that the spillover in the form of recombination of technologies upon engaging in a collaborative R&D (and thereby transfer of component recipes) is ill-tractable and most probably has a very modest effect. So, it was already remarked that the operational hypothesis is very unlikely to be observed as a consequence of the lack of adherent spillover in our operational model[3].
In subsection 5.4.3, we however also noted that the effect of externalities (in the form of having agents reverse engineer technologies already on the market) on collaboration propensity is affected by appropriability. In anticipation of the results, we argue that firms might be relying on the influx of reverse engineered technology and turn into followers. This might keep them from collaborating. It might also be so that firms might be likely to be forced to circumvent patents of technology that is reverse engineered or reap the benefit of starting from a top-fit technology. This in turn might stimulate them to collaborate.

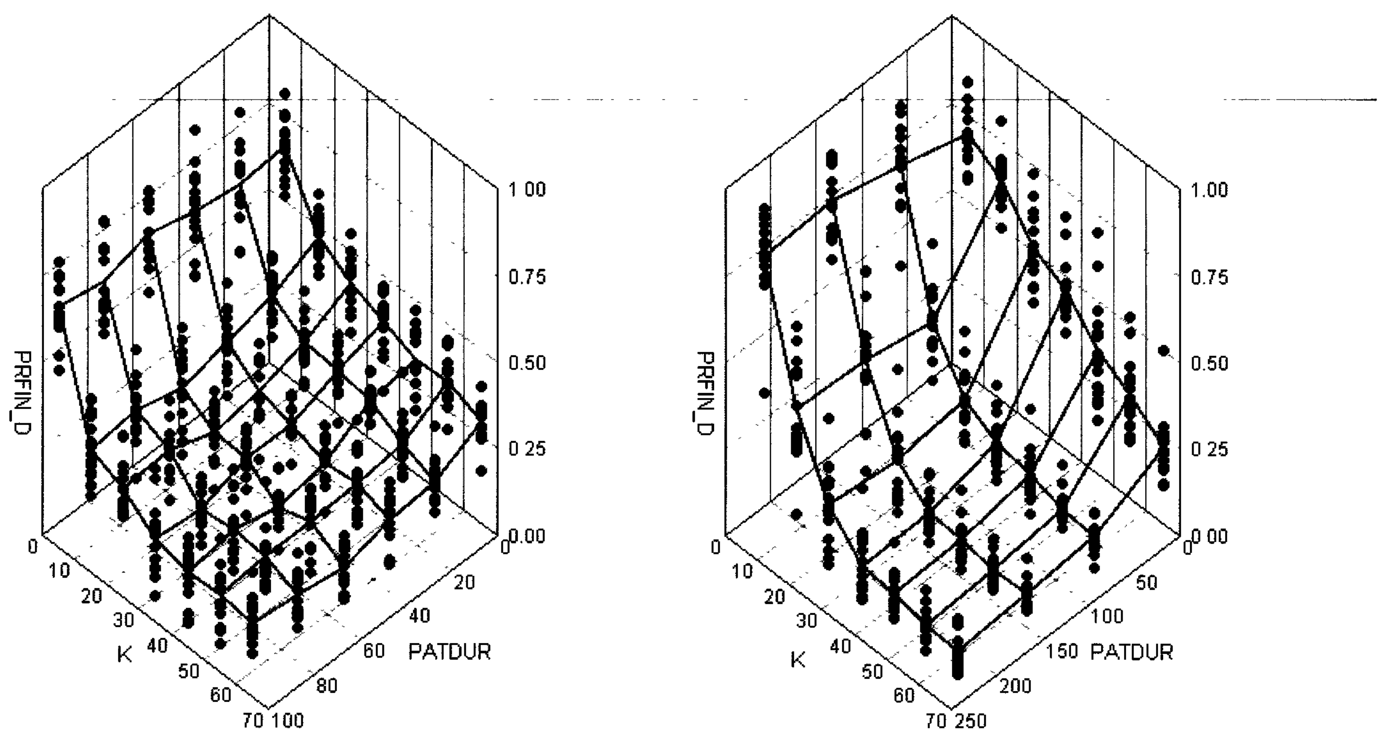
As discussed in the evaluation of the TCE framework, appropriability interacts with the other TCE factors. As far as interactions of appropriability with complexity goes, we argued in our exposition of the TCE framework that they are negatively related; design complexity is a mean to hamper reverse engineering and is as such an appropriation instrument. In our operational model, however, there is no such difficulty of engineering, so the effect of complexity (hereby mediated by the breadth of expertise) is limited to the chance of ending up in the vicinity of the technology being reverse engineered. As this chance is increasing with complexity, we expect the apparent urge to escape this neighborhood to be larger if complexity increases. We also expect this 'urge' to be amplified by the height of appropriability. Due to limited resources, we will not contest this claim in this essay, but we, however, did use this line of reasoning to come up with one of the fundamental mechanisms

2. Recall that we have removed those costs (in an early stage of the development of the operational and simulation model) to overcome the search trial length artifact of the NK landscape. We also did remove those costs because we had the impression that it played a role in not being able to reproduce the main hypothesis.
3. In our recommendations, we will indeed propose the introduction of innovation engineering knowledge such that spillover adheres in innovation performance and efficiency.

(collaboration to increase the chance on circumvention) to explain the phenomena observed in the data. We will also present some fundamental results on this issue.

6.4.2 Observations for appropriability and spillover

The simulation results of complexity K versus appropriability ω for the onset and mature phase are found in figure 6.6a and figure 6.6b respectively. We see the decrease in collaboration propensity for an increase in complexity in both figures. This, again, is caused by the complexity catastrophe. We also see that, in both figures, there is a *decreasing* effect of appropriability! Note that if there would be spillover, that instruments to appropriate the returns from R&D efforts and thereby spillover of technological knowledge would in fact realize an *increase* in collaboration propensity! After all, the negative effects of spillover would be (partially) canceled! Recall that we already stipulated in subsection 5.4.3 that we expect little or no spillover. Without further elaboration we assume that there indeed is no spillover.



(a) Onset phase, $R = 200$

(b) Mature phase, $R = 1000$

Figure 6.6: Collaboration propensity Λ for various values of K and ω for $\rho = 0.00$, $E = 40$ for the onset and mature phase

We however are surprised by an unanticipated decrease in collaboration from a baseline level of collaboration for $\omega = 0$ to nearly complete absence of collaboration if ω increases. This seems to hold not only in the mature, but also in the onset phase. The phenomenon causing this hence is in effect from the early start. Let us look at the development of the capital stock over time of agents in a sector with high appropriability $\omega = 150$ and moderate to high complexity $K = 35$, as present in figure 6.7.

We see that several 'early movers', i.e. agents that are initially in the sector or that entered early on in the simulation, tend to build a certain level of capital stock that enables them to resist market shocks. Late entrants apparently fail to gain enough market power to establish themselves as player of significance. Due to the abundant technological opportunities, early movers all have

considerable chances of finding technologies of considerable fitness eligible to enter the market. As the technology frontier is still premature, it is not so that top-fit technology is required to gain market power, so, the slightly higher chance of collaborative agents of finding top-fit technology is not crucial to survival. In this phase, agents that work solo receive more payoff (the sum of the market disbursement and the license fees) than agents that collaborate.
By the time that the technology frontier is shifting rapidly, the soloist early movers have accumulated relatively considerable levels of capital stock and although they have a lower chance than collaborative agents of finding top-fit technology, they can keep on looking for fitter technologies as they still have capital. Part of the collaborative early movers did not succeed in accumulating capital stock due to the fact that they had to share the payoff, while new entrants (who also are solo-minded) fail to get the necessary top-fit technologies.
By the time the technology frontier is maturing, the soloist early movers have found top-fit technologies themselves (although that took them relatively long), still have considerable capital stock, while hardly any late entrant forms a threat as they have a modest starting capital and thereby have only a few attempts to find top-fit technology.

If we now look at the effect of complexity, we see that again the complexity catastrophe further suppresses the collaboration propensity. However, we also see that the effect of appropriability on this 'early mover advantage' for solo-minded agents is stronger for higher levels of K. This has to do with the fact that the slightly higher innovation performance of collaborative early movers (compared to soloist early movers) diminishes with complexity. So, collaborative agents are forced into demise even sooner. For (very) low levels of complexity, the increase in innovation performance by collaborating is (very) high (see appendix B), so collaborative agents also have a high chance of building resilience. We see that this strategy of collaboration (rather than working solo) then also persists.
We in fact look at a continuum in which collaboration becomes less effective in building resilience if complexity increases. This is caused by the decrease in innovation performance augmentation of collaboration and also a decrease in the 'concealed buying' advantage.

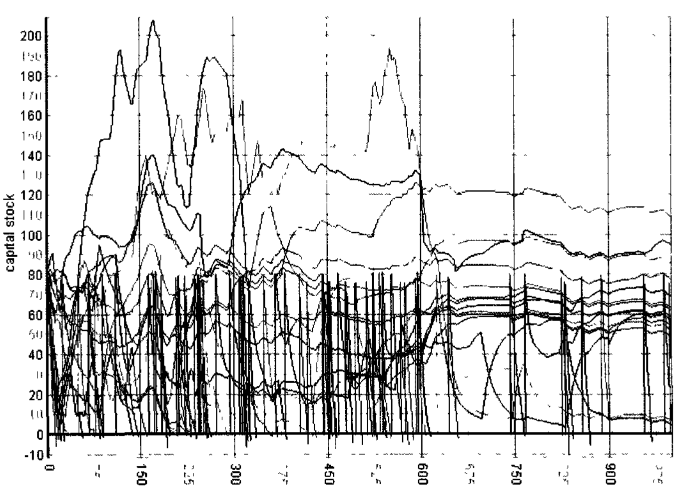


Figure 6.7: Development of capital stock of several agents over time and $K = 35$, $\omega = 150$.

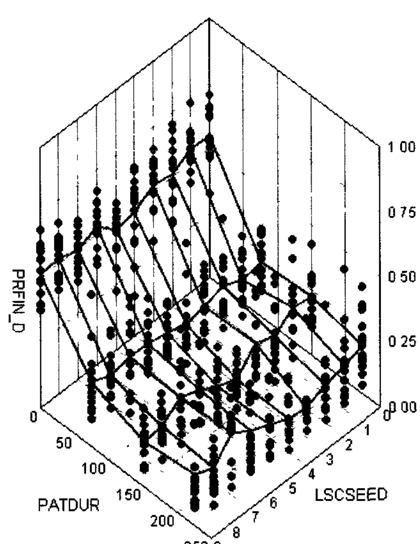


Figure 6.8: Collaboration propensity Λ for various values of ω and different landscape seeds for $E = 40$, $K = 25$, $\rho = 0$

In order to study the robustness of our findings for the landscape seed chosen, we reran the sim-

ulations for $K = 25$ for various landscape seed values. We have depicted the simulation results in figure 6.8. We calculated the Kolmogorov-Smirnov statistic for all 45 possible pairs of landscape seed indices and found only one pair (index 4 with index 7) in which the asymptotic 2-tailed significance level dropped below 5% and hence indicated a difference in distributions. We calculated the Mann-Whitney statistic and discovered that the median of the results for landscape seed 4 differs with the median of the results for four other landscape seeds (index 0, 6, 7 and 9). Admittedly, four differences on 45 pairs is quite high a number, but since especially the results of landscape seed with index 4 play a prominent role, we attribute the four differences to a coincidence.
Given the robustness for $K = 25$, we expect the results for other levels of complexity to also be robust. Given the regularities in the data and simplicity of the underlying mechanisms, we also expect the results for $R = 200$ to be robust.

Since the discussed mechanism is so basic, while we use only one implication (that there is no spillover), we omit further formal analysis of the data.

6.4.3 Observations for appropriability and externalities

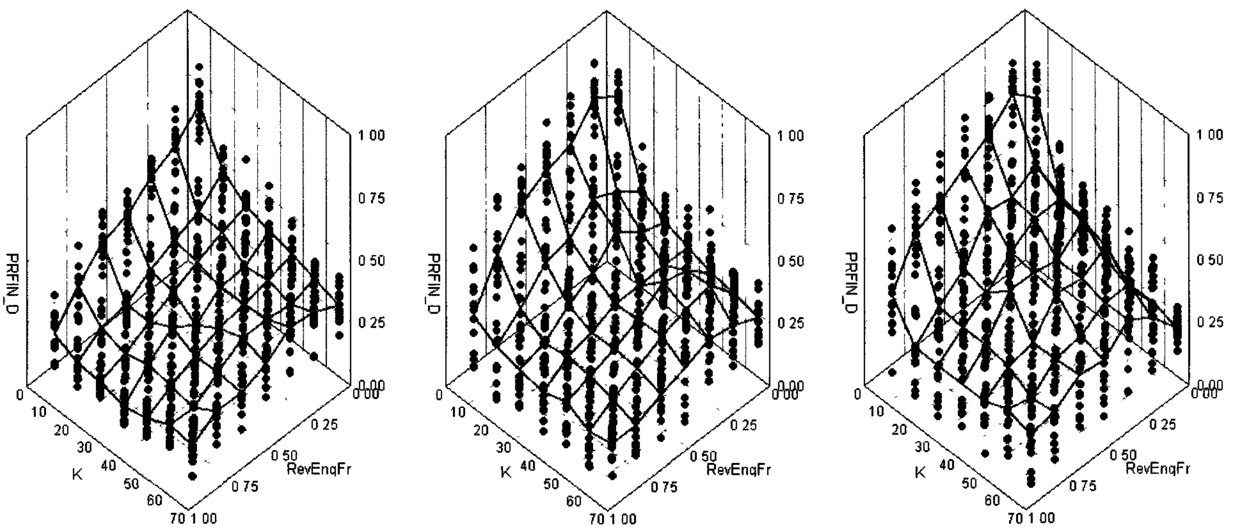
In reality, means to appropriate do not only dim the effect of spillover, also the effect of reverse ~~engineering and other externalities. In our operationalization this also holds; an agent can reverse~~ engineer a technology, but as long as it infringes the patent, the original inventor(s) and patent owner(s) can still appropriate the returns. So, let us inspect the effect of the level of reverse engineering ρ and appropriability ω on collaboration propensity Λ. This ρ is the probability that a technology on the market is reverse engineered to function as a starting point for a search trail.
We ran simulations for $\rho = 0.00, 0.15, \ldots, 0.90$, $K = 5, 15, \ldots, 65$, again with 15 seeds per pair of values. We hereby mediated for ω to inspect the intermediating effect of appropriability on the relationship between externalities and collaboration propensity. We took the values $\omega = 0, 25, 50$ for the onset phase $R = 200$ and $\omega = 0, 225$ for the mature phase $R = 1000$. We picked $\omega = 225$ so as to assure that there would still be agents enjoying patents at the end of the simulation run, not just having all agents simply suffering from the inability to patent technology due to the many patent ghosts (see subsection 5.4.2).

In the figures 6.9a, 6.9b and 6.9c, we see that, in the onset phase, there generally is a strong tendency for collaboration propensity to decrease upon an increase in the level of reverse engineering ρ. We also see that there is an increase in propensity for an increase in appropriability ω. This also holds for the mature phase, see figures 6.10a and 6.10b. We conclude that in the presence of externalities (reverse engineering), appropriability gets agents to work together more.
Another remarkable feature is that the effect of externalities seems to override the effect of the complexity catastrophe. The additional innovation performance brought about by collaboration hence is less of a benefit than simply relying on the influx of externalities.

Let us now inspect these results in more detail. There are two remarkable features of the mean grid curve: it is generally decreasing, but -dependent on the level of appropriability- there is a 'ridge' parallel to the K axis for low to moderate ρ. We will now introduce two mechanisms that will allow us to explain the collaboration propensity as a function of complexity and externality. The first mechanism relates to the advantages of being able to rely on influx of externalities, while the second mechanism is in fact a composition of various extra-ordinary evolutionary advantages of collaboration when having reverse engineered technology at disposal.

Externality-opportunism

The first mechanism is related to the fact that agents are increasingly independent of the incoming technological knowledge through collaboration if there is a higher degree of externality. The more



(a) $\omega = 0$ (b) $\omega = 25$ (c) $\omega = 50$

Figure 6.9: Collaboration propensity Λ for various values of K and ρ for $E = 40$ and $R = 200$, for various levels of appropriability

reverse engineering, the less agents depend on own innovation performance and the less required the additional increase in fitness resulting from collaboration in their survival, so the less collaboration in fact emerges. Let us refer to this as 'externality-opportunism'.

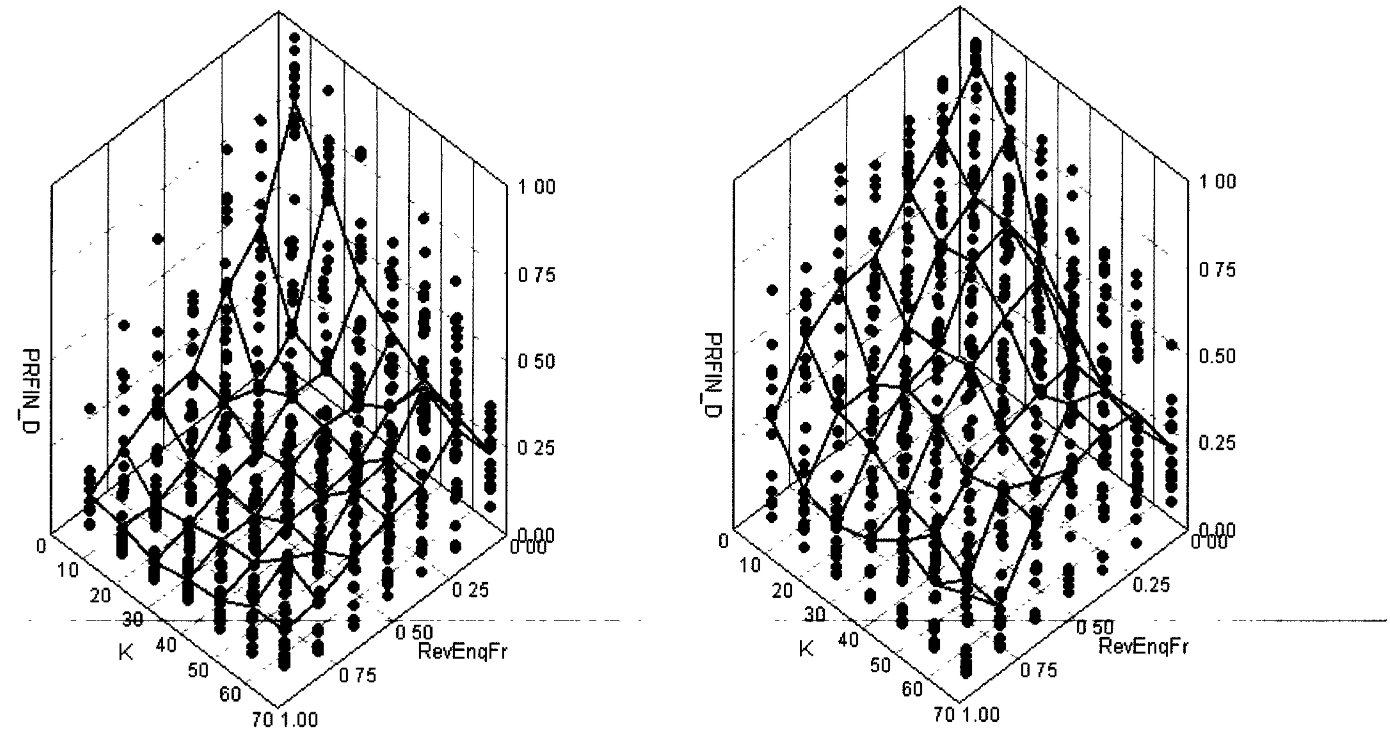
In this case, we can however not use a degenerate, fundamental version of our simulation model to analyze the fitness values (that are obtained when agents either collaborate or are either working solo) for different values of ρ (and as such to explain the incentive to collaborate). Here, the innovation results after all strongly depend on the technologies on the market, while the state of the market is in turn affected by all other agents in the system. So, to check whether the externality-opportunism mechanism is at stake by the fitness values obtained would in fact require about our whole simulation model again.

We furthermore argue that relying on influx of externalities, i.e. following an externality-opportunistic strategy, is (of course) less effective if the agents reverse engineer little. If ρ is low, agents reverse engineer a technology only occasionally. In order to build up market power and resilience, agents still have to produce technologies of sufficient fitness. Note that they also have to do build up resilience because other agents also occasionally reverse engineering a technology on the market and hence also put pressure on performance of other agents. We hence argue that under moderate externalities, agents cannot rely on externality-opportunism. As soon as ρ becomes large, the technology frontier develops fast, agents can rely (more) on influx of externalities. Agents hence are becoming less dependent on own performance and less dependent on the contribution of collaborators (and this even becomes less significant because the frontier is more developed anyway). Although we cannot discern that from the data, it might even be so that they can better safeguard the additional payoff by working solo.

We will introduce this slope downward of collaboration propensity in an increase of ρ by first specifying the model in 6.3 for fixed $\bar{E}$ and then multiplying with a general term $(\rho^* - \bar{\rho})^{\beta_1}$. Hereby $\bar{\rho}$ is a mapping of the ρ values we use in the simulation $\rho = \{0, 0.15, \ldots, 0.90\}$ onto $\{1, 2, \ldots, 7\}$ and ρ^* is the maximum value of $\bar{\rho}$ plus one (such that $(\rho^* - \bar{\rho}) > 0$ for all $\bar{\rho}$).

Since we fix $E = 40$, we fill out the right-hand side of model 6.3 to obtain:

$$\Lambda \leftarrow \alpha(\alpha_0 - (\bar{E} - \alpha_1)^2)e^{\alpha_2(1-\bar{K})} + \beta(\bar{E}^* - \bar{E})^{\beta_0}\bar{K}^{\beta_1}$$



(a) $\omega = 0$ (b) $\omega = 225$

Figure 6.10: Collaboration propensity Λ for various values of K and ρ for $E = 40$ and $R = 1000$, for various levels of appropriability

$$\Rightarrow \quad \{\text{Specific, fixed } \bar{E} \text{ value}\}$$

$$\Lambda \quad \leftarrow \quad \pi e^{\pi_1(1-\bar{K})} + \pi_2 \bar{K}^{\pi_3} \tag{6.4}$$

We thus obtain the following model term:

$$\Lambda \leftarrow (\alpha e^{\alpha_1(1-\bar{K})} + \alpha_2 \bar{K}^{\alpha_3})(\rho^* - \bar{\rho})^{\beta_1} \tag{6.5}$$

We see that if $\beta_1 > 0$, then $(\rho^* - \bar{\rho})^{\beta_1}$ is decreasing and indeed the whole term goes to zero. An attentive reader might have noticed that we are talking about a *decrease* in collaboration propensity for an *increase* in ρ. We could have chosen to introduce a base propensity term $A(K)$ (i.e. that when $\rho = 0$) and a negative (and independent) term $-B(\rho)$ to represent the decreasing urge of an agent to collaborate when this agent can rely more on externalities. This would hence give the composite term $A(K) - B(\rho)$. We, however, have assumed that the drop in collaboration propensity due to externality-opportunism is *proportional* to the base propensity.

Exploitation of head start and patent circumvention

The second mechanism is that collaboration is an effective mean to build up resilience. We have found two additional benefits of collaboration in a situation with externalities that over and above ordinary effects on innovation performance stimulate the propensity to collaborate. As the phenomena cannot be discerned in the data, there might be even more phenomena. Firstly, collaboration enables agents to exploit the head start that a reverse engineered technology provides. Secondly, collaboration enables agents to circumvent patents protecting the reverse engineered technology and increases the probability of getting one themselves. Let us now elaborate on both. In addition, we also expected the collaboration propensity resulting from 'concealed buying' to be effective.

The first effect of collaboration is that it effectively exploits the head start. We have studied the technicalities in appendix D and will evaluate the findings here briefly. The increase in innovation performance that is established by working collaboratively rather than working solo is -in expectation- absolutely larger if the starting technology is fresh rather than reverse engineered. This however is caused by the fact that it is increasingly hard to improve technology that already is relatively fit. Although collaboration will in both cases yield -in expectation- technology that is fitter than the technology the R&D project started out with, the *global* fitness of the final optimum is in the latter case -in expectation- higher than in the earlier case. We hence discovered that, starting from fresh technology, collaboration will yield a considerable improvement, but the obtained technology is very likely to be (slightly) less fit than any technology reverse engineered from the market. Although adjustments to the reverse engineered technology does not always bring about an increase in global fitness, it still is very likely this technology produced from a fresh invention has a fitness which is less than an adjusted reverse engineered technology, especially when it is improved in collaboration. So, reverse engineered technology gives a head start that is most effectively made use of by collaboration. If appropriability increases, having the patent on a top-fit technology of course greatly increases chances of survival, so it is then even more important to exploit that head start advantage.
This 'exploitation of the head start by collaboration' of course is thwarted by an increase in the level of externalities as this reduces the relative advantage of an incidental discovery of a top-fit technology; the probability of finding one strongly increases for all agents. Note furthermore that if the level of externalities increases, not only does the exploitation strategy becomes less effective, also the externality-opportunism strategy becomes increasingly effective. Both developments make collaboration less likely.

The second effect of collaboration is that it increases the chances of circumventing the patents protecting the reverse engineered technology. We have studied the fundamental properties of this mechanism in appendix E and we will evaluate the findings here. Let us, first of all, establish that it is better for an agent to have the patent on technology being reverse engineered by other agents than reverse engineer a technology and having to pay the license fee for it. The probability of ending up infringing a patent of a reverse engineered technology increases with complexity as the Hamming distance between the reverse engineered technology and the finally obtained optimum decreases.
The fundamental results show that if complexity is low, agents collaborating but also agents working alone are able to circumvent the patent protecting the reverse engineered technology, so collaboration has no additional benefit in this respect.
If complexity is moderate to high, agents working solo are caught soon in a basin of attraction close to the technology they reverse engineer. Collaborating then has two benefits. First of all, there is a reason related to the properties of the search procedure (see subsection 5.2.2). If agents collaborate, they form a super-agent with a wide field of expertise. The alliance has more control over technological elements, and is thereby able to escape a (possibly) poor basin of attraction. This suggests that collaboration might yield a longer trajectory (and thereby a greater Hamming distance between reverse engineered technology and final optimum) as the alliance can escape the basin in which it would otherwise be locked. Second of all, there is a reason related to the matching procedure and more particularly to the initial changes and the following amendment proposal (see section 5.3). In the first step of the algorithm, the principal agent considers changes to the reverse engineered technology T_i^I. This might very well be $T_i^P = T_i^I \otimes_{E_i} T_i^*$ and indeed we expect a certain displacement in the landscape and hence a certain increase in the Hamming distance. In the second step, the potential collaborators provide amendments, i.e. $T_i^P \otimes_{E_j} T_j^*$. Again, we expect a certain displacement and possibly a increase in Hamming distance. So, if the principal agent ends up collaborating after either changing the initial, reverse engineered technology or after a change

by the collaborator, there already is a certain Hamming distance expected. This also increases the chance of ending up in an alternative optimum. We see that collaborating not only makes the collective more likely to have a longer walk than an agent alone, the initial change and suggested amendment are also likely to add to the Hamming distance. If complexity is high, collaborators hence are (way more) likely than agents working solo to circumvent the patent on the technology reverse engineered.

If we now look at the net effect of both consequences of collaboration, we see that exploitation of the head start is primarily effective if the level of externalities is low to moderate, while collaborating for patent circumvention is primarily effective if complexity is moderate to high. We already know that the 'concealed buying' is most effective for low to moderate complexity. If we inspect the figures again, we indeed see that most of the action is for low to moderate levels of externalities upon an increase in appropriability.
As we cannot disentangle the effects, we will introduce a term representing the combination of exploitation of head start and patent circumvention in the following, rather indefinite form:

$$\Lambda \leftarrow \beta(\gamma_0\bar{\rho}/\rho^*)^{\beta_2}e^{-\gamma_0\bar{\rho}/\rho^*}(\gamma_1(\bar{K}^* - \bar{K}))^{\beta_3}e^{-\gamma_1(\bar{K}^*-\bar{K})} \tag{6.6}$$

This is the product of two gamma-like functions. As we will see, it will introduce bumps that generally account for the introduction of the down-sloping ridge from $\rho = 0.15$ onward.

We see that with an increase in appropriability, the whole 'mean grid' surface shifts upward, regardless of whether we look at the onset or the mature phase results. We hence observe that appropriability ω indeed increases collaboration propensity Λ if there is externality $\rho > 0$. It becomes, on the one hand, increasingly attractive to try to obtain top-fit technology with the help of a collaborator as sharing the returns is interesting due to the appropriability, and, on the other hand, increasingly necessary to circumvent patents as they last longer. Sharing income of technology of which you jointly own the patent is financially more attractive than having of income of licensed technology.

6.4.4 Fitting the regression model

We can join the model term for the effect of the externality-opportunism strategy and the model term for the extra-ordinary evolutionary advantages of collaboration (exploitation of the head start and patent circumvention) to form the following model:

$$\begin{aligned}\Lambda \quad \leftarrow \quad & (\alpha e^{\alpha_0(1-\bar{K})} + \alpha_2\bar{K}^{\alpha_3})(\rho^* - \bar{\rho})^{\alpha_1} + \\ & \gamma(\sigma_1\bar{\rho}/\rho^*)^{\nu_1}e^{-\sigma_1\bar{\rho}/\rho^*}(\sigma_2(\bar{K}^* - \bar{K}))^{\nu_2}e^{-\sigma_2(\bar{K}^*-\bar{K})}\end{aligned} \tag{6.7}$$

We now fit this model to the sets of simulation data and obtain the coefficient estimates present in table 6.2 (with the t-value of the coefficient estimate between brackets).

The fit for the models for $R = 200$ is reasonable with R^2 around 0.56. The models for $R = 1000$ suffer a poor fit with R^2 around 0.36. Looking at the figures for $R = 1000$, we see that the measured Λ values indeed are highly dispersed. This is not purely to be taken as an indication we have to tune model parameters to increase the evolutionary force. This observation is also conceptually relevant. Due to reverse engineering and appropriability, and the strongly developed technology frontier, features other than just collaboration strategy are at stake. The factor of luck, how corny that may sound, actually strongly determines which agent(s) is (are) dominating. Especially in the case of high appropriability, agents that obtain relatively fit technologies by accidental discovery immediately turn into agents with considerable (market) power. These agents are certain of a considerable payoff at least ω periods, which gives them great resilience for developments and many opportunities to gain new technologies especially in combination with high levels of reverse engineering.

	$\omega = 0$ $R = 200$	$\omega = 25$ $R = 200$	$\omega = 50$ $R = 200$	$\omega = 0$ $R = 1000$	$\omega = 225$ $R = 1000$
α	0.0923 (3.08)	0.210 (2.17)	0.236 (2.52)	0.0317 (1.52)	0.280 (0.17)
α_0	1.044 (3.56)	0.953 (2.94)	0.960 (1.84)	0.777 (0.91)	0.219 (0.33)
α_1	0.633 (8.87)	0.356 (9.08)	0.240 (7.06)	1.314 (12.17)	0.540 (9.88)
α_2	1.030 (1.53)	0.618 (0.82)	0.708 (0.76)	0.641 (0.36)	0.000 (0.00)
α_3	0.000 (0.00)	.00305 (0.0075)	0.000 (0.00)	0.000 (0.00)	0.627 (5.52)
γ	0.280 (0.42)	0.0271 (0.26)	.00676 (0.32)	0.0000472 (0.11)	0.000606 (0.15)
σ_1	0.335 (0.69)	1.508 (2.06)	1.839 (3.36)	1.728 (1.78)	2.269 (2.09)
ν_1	2.293 (0.85)	4.673 (1.98)	5.669 (3.25)	5.327 (1.58)	6.997 (2.00)
σ_2	0.525 (1.04)	0.355 (1.46)	0.495 (2.36)	3.815 (1.65)	0.387 (1.09)
ν_2	0.587 (0.65)	1.133 (1.39)	1.804 (2.37)	5.964 (1.69)	0.288 (0.37)
R^2	0.640	0.572	0.520	0.357	0.365

Table 6.2: Model coefficients and their t-value and R^2_{adj} for K versus ρ for various levels of ω

From the low coefficient of γ in combination with low t-value, we can tell that the effect of the exploitation/ patent circumvention factor is modest, which we can visually confirm. It must be said that there always some interaction between coefficients due to the regression estimation techniques. This means that some of the effect is measured by other model terms and we have to be careful with interpreting the magnitude of coefficients. Still, despite the modest coefficients, the prompt increase in the t-values and the coefficient estimates for σ_1, ν_1, σ_2 and ν_2 upon an increase in ω forces us to conclude that the compound alternative collaboration effects (exploitation and circumvention) become more prominent nonetheless. So, if appropriability increases, it becomes more crucial in survival to exploit the head start and circumvent patents. Note that this just confirms the expectations we expressed earlier. We see that similar phenomena occur in the mature phase ($R = 1000$) if we increase appropriability although the term as a whole becomes even less significant as the t-value for γ further drops.

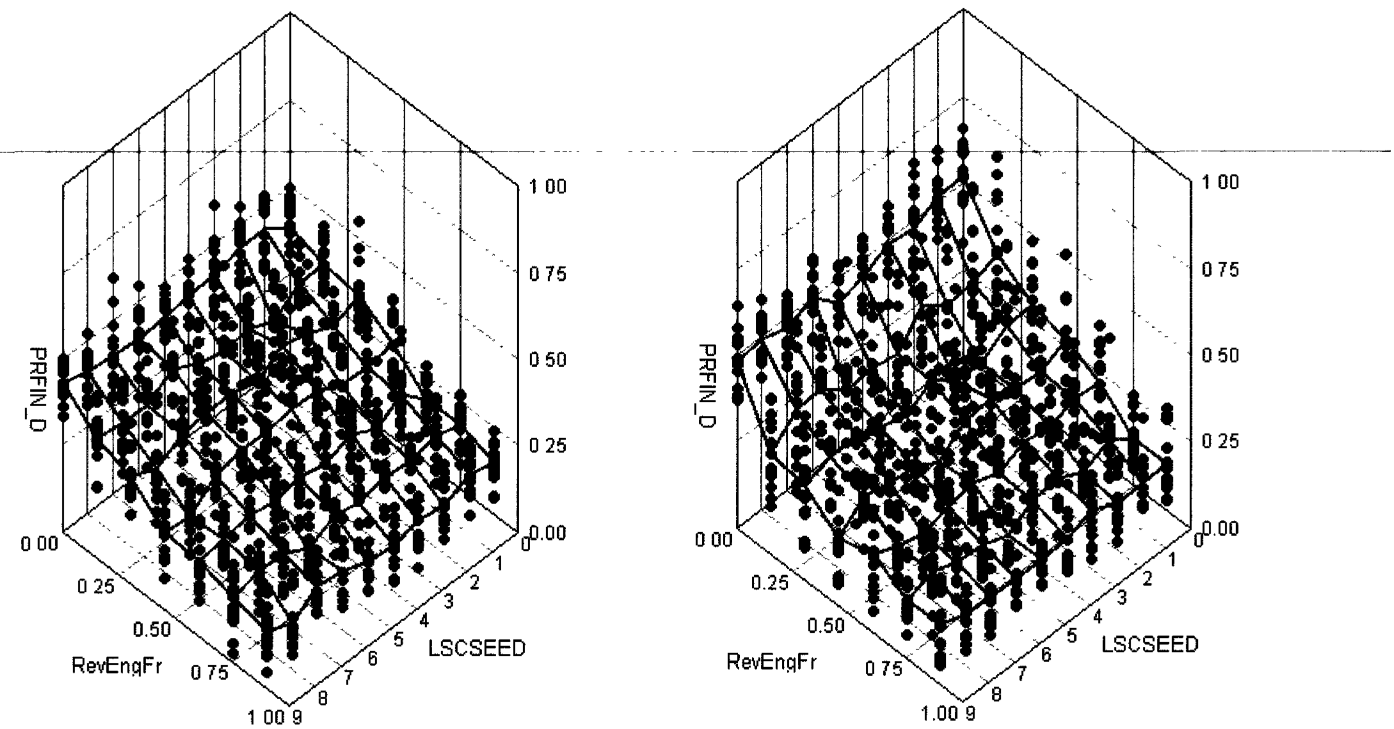
Note furthermore that especially the ν_1 coefficient is generally relatively high (while the transformed variables $\bar{\rho}/\rho^*$ and $\bar{K}^* - \bar{K}$ are scaled such that we can actually compare these subterms and coefficients in magnitude). We hence are inclined to conclude that especially collaboration to exploit the head start resonates in the data.

As far as the externality-opportunism term goes, we observe that it is clearly present as α is significant in most cases (except for $\omega = 225$, we will elaborate on that later). We have to be aware that this term however also contains the ordinary collaboration propensity and therefore also sheds the shift in propensity for a change in appropriability. Further note that the drop in propensity for an increase in ρ compared to the base propensity for $\rho = 0$ reflects the increase in relying on externalities. We see that, due to the high t-values, that α_1 is considerably important in explaining the variation in the data. This α_1 in fact determines the curvature of the effect of externalities on collaboration propensity. From the overall decrease in the height of the $\alpha, \alpha_1, \ldots, \alpha_3$ coefficients for an increase in appropriability, we conclude that upon an increase in appropriability, the externality opportunity strategy becomes less effective. This indeed confirms our expectations. We also see that, since α_3 is about zero in all models (apart from the case with $\omega = 225$), the role of the effect describing the interaction of complexity with 'ill-appraisal' is virtually absent which is supposedly caused by the high value of E. We see that the term $\alpha_2\bar{K}^{\alpha_3}$ then is reduced to a constant displacement in propensity. The low value for α in combination with the high value for α_3 in the $\omega = 225$ simulation is argued to be an interaction of the coefficients due to the non-linear regression estimation procedures.

6.4.5 Robustness for landscape seeds

At a quick glance, figures 6.11a and 6.11b tell us that there is little variation for landscape seeds. For $R = 200$, the Mann-Whitney statistic indicates that the results for landscape seed 8 differs significantly from the results for landscape seed 1 and 3. So, all in all, there are only 2 out of 45 combinations in which we are compelled to reject that the medians are equal. There also is a significant difference between the results for landscape seed 3 and 8 in the Kolmogorov-Smirnov statistic. So, not only the medians are not equal, we also do not find support for equality of the distributions.

For $R = 1000$, we see that the Mann-Whitney and Kolmogorov-Smirnov tests have us conclude that both the median and the distribution for landscape seed 5 differs from the medians and distributions for landscape seed 3 and 8.



(a) $R = 200$ (b) $R = 1000$

Figure 6.11: Collaboration propensity Λ for various values of K and landscape seeds with $\rho = 0$, $\omega = 0$, $E = 40$ for the onset and the mature phase

It should be clear that, since we test at a significance level of 5 percent, one or two odd cases are in line of expectations. We conclude that there is no evidence that the effects of reverse engineering on the collaboration propensity (under the conditions of no patenting) are not robust for the landscape seed chosen. The statistics have us claim that the results are robust for the landscape seed chosen.

6.4.6 Evaluation

Our (supposedly robust) simulation results in the first place confirmed that appropriability has no positive effect on collaboration propensity (in simulations without externalities). This concurs with the claim posed earlier that spillover is absent in our operational model. We however did find something we called the 'early mover advantage' that allows initial and early entrants to build up (financial) resilience and thereby outperform late entrants and agents that follow a different strategy. If complexity is moderate to high, solo-minded agents enjoy this early mover advantage, while, if complexity is low, collaborative agents enjoy this early mover advantage.

We turned to the mediating effect of appropriability on the relationship between externalities and collaboration propensity. We discovered that the collaboration propensity in fact is shaped by an inclination toward externality-opportunism and a composition of factors that aid in building resilience (we examined and discerned two mechanisms: exploitation and patent circumvention). An increase in externalities allows agents to rely on externality-opportunism more. On the other hand, there is a disincentive for sharing the short-lived, early 'monopolistic' returns that counterbalances the additional building of resilience through exploitation and patent circumventing. This causes a slight distortion when moving from a situation in which there are no externalities ($\rho = 0$) to even a situation in which there is only a low level of externalities. Agents simply benefit from exploiting the externalities. Still, all in all, in isolation and absence of appropriability, agents are inclined to collaborate less if the level of externalities increases. Leaving the distortion at $\rho = 0$ for the moment, we hence discovered that $\rho \xrightarrow{-} \Lambda$.

We furthermore saw that with an increase in appropriability, the effectiveness of externality-opportunism diminishes, while both exploitation and patent circumvention become more crucial in performance. Appropriability positively affects the collaboration propensity. So, given that $\rho > 0$, $\omega \xrightarrow{+} \Lambda$.

The effect of externalities is so strong that it already manifests itself in the onset phase in weeding out promptly the ill-performing collaboration strategies. We see however that in the mature phase, there is more variation in collaboration strategies. This is caused by the fact that the agents face a sector that has very few opportunities for patenting and most patents on top-fit technologies have expired, so instruments to appropriate are ineffective and agents have little benefit of their own innovation performance. Survival and hence persistence of certain strategies are also characterized by a degree of chance and coincidence of finding the right technology at the right point in time.

6.5 Level of Competition and Complexity

We will again follow the method described in section 6.2 to study the effect of the operationalization D of the factor level of competition of the TCE model in conjunction with the effect of the operationalization K of the factor technological complexity on the measure Λ for collaboration propensity.

We will first recap the hypothesis and the issues at stake that might hamper this hypothesis from being confirmed. We will then briefly describe the phenomena observed, propose fundamental mechanisms that account for these phenomena and formulate mathematical terms for the non-linear regression model. We will then fit the regression model and evaluate the coefficients in the light of our hypothesis. We will also check the robustness of the results. Finally, we will evaluate the findings in the light of our hypothesis.

6.5.1 Hypothesis

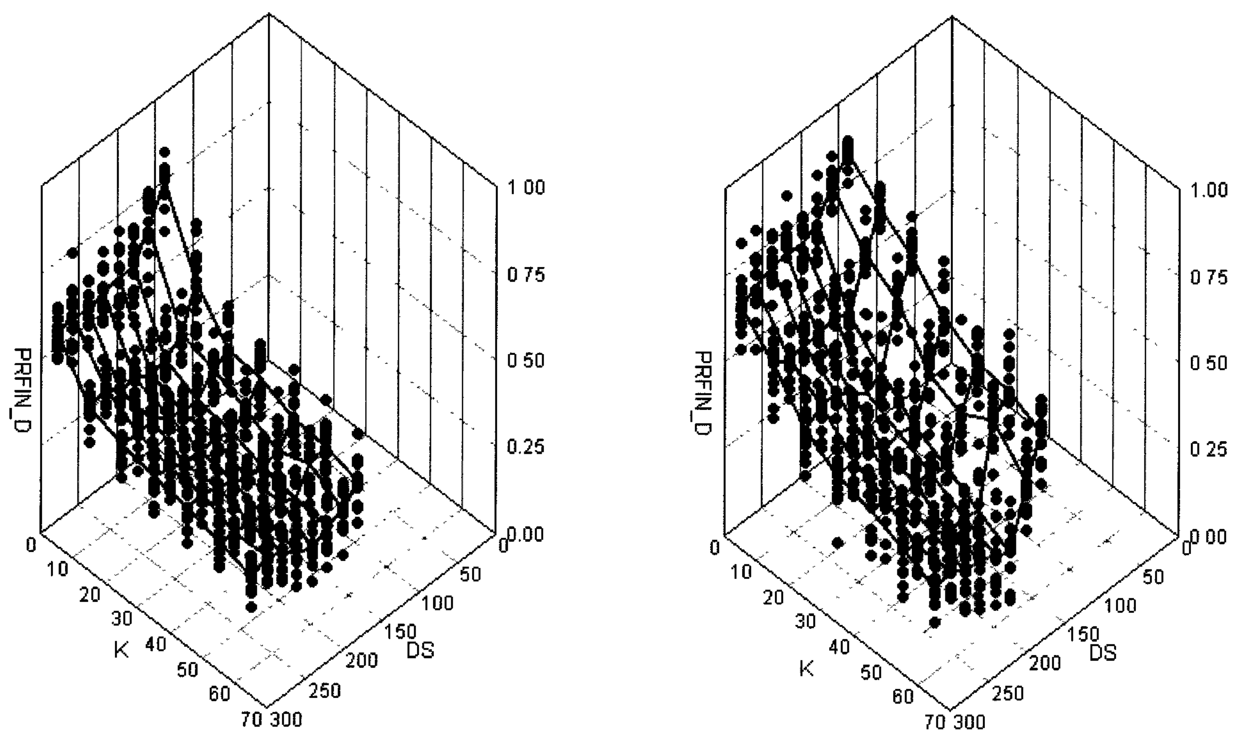
From the exposition of the adorned TCE framework in subsection 2.3.1, we know that, on the one hand, the negative effect of non-appropriable spillover on market performance is amplified by the level of competition, but that, on the other hand, the positive effect of (synergistic) complementary knowledge on innovation performance can prove to be crucial in survival. So, obviously, if the contribution to dynamic efficiency of the synergistic benefits outweighs the negative effects of outgoing non-appropriable spillover, the collaboration propensity of firms is argued to be positive, especially when competition is fierce.

We have operationalized the level of competition as the demand size D being the total amount of

credits that is disbursed each period (see the definition of the operational market model in equation 5.8). If there is a lot to be divided among the agents (D is large), even agents that produce technologies of poor fitness will receive a large amount. If there is little to be divided among the agents (D is small), agents that produce technologies of poor fitness will have a hard time recovering their fixed costs. This will thereby reduce their chances of long-term survival and agents are reluctant to share the crucial piece of the pie. If D decreases, we interpret this as if there is more competition. So, the general expectations are that if competition rises, collaboration propensity decreases, i.e. $D \xrightarrow{+} \Lambda$. Hereby, we however have assumed a moderate, but significant presence of spillover.
In subsection 5.4.3, we already noted that (a.o. due to our limited conception of innovation capabilities) spillover in terms of something affecting the dynamic efficiency is as good as absent. We then see that the consideration only concerns the marginal increase in fitness versus the having to share the payoff. We hence expect the negative effect for a decrease in market size (i.e. an increase in level of competition) to be dimmed. As a consequence we are no longer sure about the uniformity of the change as there appears to be a leveling off of the diminishing or even a total curb in collaboration propensity Λ for a decrease in D.

6.5.2 Verbal account of results and suggested underlying causes

We run an ordinary set of simulations for $K = \{5, 15, \ldots, 65\}$ and $D = \{100, 150, 200, 250\}$ and the result is plotted in figures 6.12a and 6.12b.



(a) $R = 200$

(b) $R = 1000$

Figure 6.12: Collaboration propensity for various values of K and D for $E = 40$, $\rho = 0$, $\omega = 0$

If we now look at the effect of demand size, we see that collaboration propensity -on average- *increases* strongly with a decrease in demand size, that is, if $D <= 200$. This is exactly the opposite of what we expect from the theories of Von Hippel! The most likely explanation is then that of Sakakibara: collaboration strengthens the competitive position of the agents. As this would indeed be more required in a more competitive market, one should expect more collaboration if the

demand size decreases!
For $D > 200$, we see that the effect of variation of D is nearly insignificant, perhaps apart from a slight increase in a rise in D for high levels of complexity. We would attribute this last slight increase to a sort of evolutionary leniency toward agents that perform less as this does not (or only in the long run) manifest itself in bankruptcy as the payoff totally or, at least, nearly outweighs the fixed costs.

If we look at the development of Λ for changes in K, we see that there is a steady decrease over all levels of D. We argue this decrease again stems from the complexity catastrophe, its pressing effect on maximum attainable fitness and thereby the viability of collaboration.
We also see that there is little to no interaction between the level of competition and the complexity in determining the collaboration propensity.

Required innovation performance

We explain the results from one and the same mechanism. If competition is fierce i.e. if demand size is low (and there is no non-appropriable spillover), then agents seek collaboration for complementary capabilities in order to increase innovation performance. This is in line with Sakakibara. If, on the other hand, the demand size is exorbitantly high, agents do no longer have to be dynamically efficient as even mediocre or poorly fit technologies allow them to, at least, cover the fixed costs. There is insufficient punishment of particular strategies as they simply nearly all survive. So, the leniency toward collaboration comes with the luxury of high demand size. So, on the one side of the continuum of the demand size spectrum, agents are forced to collaborate to increase chances of survival, while on the other side of the continuum, agents most strategies will survive, including collaboration.

We already observed that the decrease in complexity stems from the complexity catastrophe. We also argue that the shifts in collaboration propensity are due to market pressure and that there is little to no interaction between the magnitude of this shift and the level of complexity.
To reflect the independence between the complexity catastrophe and the 'required innovation performance' mechanism, we introduce two separate terms in our regression model. The first term accounts for the development of collaboration propensity under changes in complexity (here, that simply is the complexity catastrophe effect) is again derived from equation 6.3 filled out for a specific E. We obtain: $\Lambda \leftarrow \beta e^{\beta_0(1-K)} + \gamma K^{\gamma_0}$. The second term accounts for the development of collaboration propensity for changes to the demand size (and nothing more) and we have decided to introduce this as the generic term $\Lambda \leftarrow \alpha/(1+e^{-\alpha_0(1-D)})$. This formula allows for a steep rise from nearly zero to nearly one which we will need to describe the strong curbing that occurs if D decreases below 200.

6.5.3 Fitting the regression model

We come to the following regression model:

$$\Lambda \leftarrow \alpha/(1+e^{-\alpha_0(1-D)}) + \beta e^{\beta_0(1-K)} + \gamma K^{\gamma_0} \qquad (6.8)$$

As the left term accounting for the Sakakibara shift in propensity does not contain K and the right term does not contain D, there is no assumption of interaction in the regression model. If we fit this model to the data, we obtain the coefficient estimates as presented in table 6.3 (with between brackets the t-value of the coefficient estimates). Since we have relatively high R^2 values in both cases, the fit is to be considered good. The high R^2 is partially caused by the extremely low variance in the outcome due to which a proper model also immediate explains much of the variance.
We see that the steep increase is highly significant as the t-values for α and α_0 by far exceed the threshold of two (standard deviations). We also see that the decrease in collaboration propensity

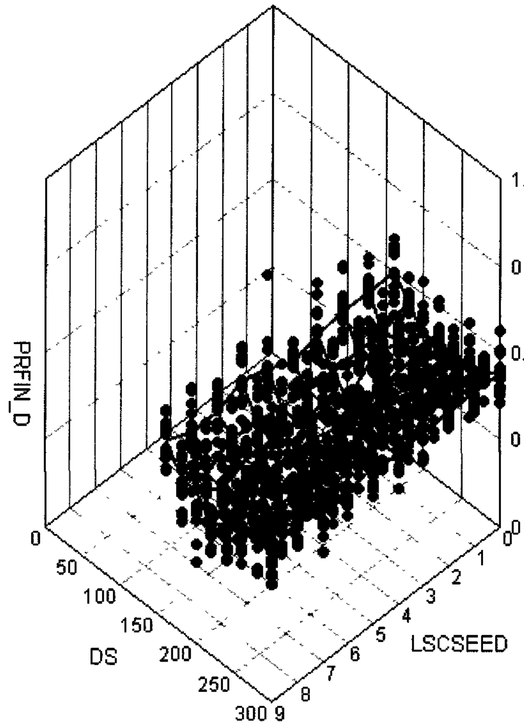
	$R = 200$	$R = 1000$
α	0.176 (12.22)	0.478 (27.14)
α_0	2.00 (5.17)	1.332 (13.03)
β	0.302 (3.80)	0.514 (2.24)
β_0	0.749 (5.85)	0.298 (9.40)
γ	0.340 (4.24)	0.209 (0.904)
γ_0	0.000 (0.00)	0.000 (0.000)
R^2	0.705	0.793

Table 6.3: Model coefficients and their t-value and R^2_{adj} for K versus D for both the onset and mature phase

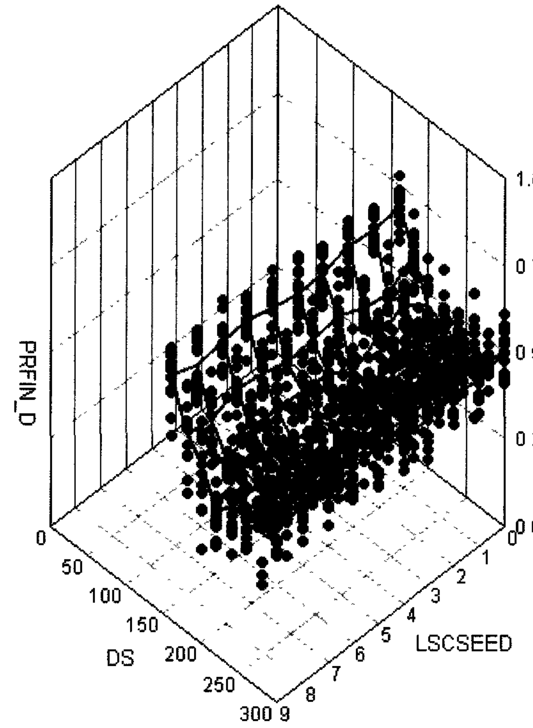
explained by the complexity catastrophe is highly significant (the t-values for β and β_0 are high). The last term accounting for the interaction of K and E in ill-appraisal however is reduced to a mere constant shift due to the low γ_0 value and the insignificance of the estimate in explaining the variance.
We also see that with an increase in R, i.e. when moving from the onset phase to the mature phase, the Sakakibara shift becomes more significant. The reason for that is sought in that there has been a longer period of evolutionary pressure on the collaboration strategies which apparently further emphasized the evolutionary benefits of collaboration for survival in that situation of scarcity.

6.5.4 Robustness for landscape seed

As we can see in figure 6.13a and figure 6.13b, the results appear to depend only little on the landscape seed chosen. If we run the usual non-parametric tests on the dataset for $R = 200$ depicted



(a) $R = 200$



(b) $R = 1000$

Figure 6.13: Collaboration propensity Λ for various values of D and landscape seeds for $K = 25$, $\rho = 0$, $\omega = 0$, $E = 40$

in figure 6.13a, we find no significant differences in the distributions according to the Kolmogorov-Smirnov statistic and no significant differences in the medians according to the Mann-Whitney statistic. If we do the same on the dataset for $R = 1000$ depicted in figure 6.13b, we find no significant differences in the median according the Mann-Whitney statistic and only in one case a significant difference in the distributions according to the Kolmogorov-Smirnov statistic (in case we compare the data for landscape seed index 0 and index 1). We conclude that the outcome is robust for the choice of landscape seed.

6.5.5 Evaluation

We see that our (supposedly robust) simulation results indicate that collaboration propensity increases with the level of competition, i.e. $D \stackrel{-}{\rightarrow} \Lambda$. Due to the absence of non-appropriable spillover, there is no risk of opportunism in collaboration. Collaboration strategies are then only selected on the net effect of additional payoff and having to share this payoff. Due to our choice for Q^0 and C, the agents have only a few goes to obtain technologies to fully cover the fixed costs. If competition is fierce (D is low), getting sufficient payoff becomes increasingly difficult and agents have get relatively fit technology even faster or their technology should be fitter. Here, collaboration increases the chance of discovering a technology fit enough to enter the market, so we indeed find a high level of collaboration propensity.
In extremum, if competition is *so* fierce (D is so low) that only a small fraction of the agents is able to cover their fixed costs, a strategy that would only keep the agent alive for a few more periods would have a considerably higher chance of being imitated. So, although agents are likely to perish in only a few periods anyhow, the strategy that postpones bankruptcy as long as possible will emerge.
From the results we conclude that the proportional share of payoff from the relatively fitter technology obtained through collaboration is -at least initially- apparently larger than the whole payoff from the relatively less fit technology obtained in solo. This allows the strategy population to tip to collaboration. From the persistent nature of this strategy (small variance) even in the mature phase we conclude that this rationale holds even when the technology frontier has further progressed.
If, on the other hand, D is high, agents have little risk of perishing as even poor fit technologies generate payoff that enables the agents to cover the fixed costs C.

6.6 Evaluation of simulation results

In short, we have developed a conceptual TCE model to predict collaboration propensity from several disaggregated factors determining uncertainty. We have then operationalized this TCE model within a Neo-Schumpeterian framework such that R&D collaboration behavior determined by the TCE factor operationalizations can dynamically emerge during simulation runs. After thorough experimentation, we have selected a set of starting parameters and have subsequently experimentally varied the values of the TCE factor operationalizations. We have thus gathered the 'empirical' simulation data, inferred on the causes of the observed phenomena through reduced versions of our simulation model, formulated econometric models reflecting these causes (mechanisms) and used regression analysis to show that we can indeed explain considerable variance in the data.
Here, we will only shortly sum the findings from the simulation per TCE factor. We will interpret the findings on the operational hypotheses in the realm of the TCE theory in the next chapter thereby bearing in mind the shortcomings of our operationalizations as signaled.

As far as the factors *complementarity* and *complexity* and their interaction are concerned, we have observed that our model does not confirm the central hypothesis that collaboration propensity increases with complexity. This is caused by the complexity catastrophe property of the NK landscape model. The benefits we accrue to collaboration propensity from our definition of technological

complexity are superposed by a drop in attractiveness of collaboration for synergistic innovation performance augmentation for an increase in intricacy K due to the complexity catastrophe. We consider this an artifact of our operationalization. We also observed that agents tend to do a 'concealed buying' of complementary components if complexity is low.
We also have seen that in the onset phase, the set of agent strategies is yet insufficiently shaped and that collaboration occurs more often than predicted by the actual innovation performance augmentation (in terms of an increase in fitness by collaborating rather than working solo). This is caused by 'ill-appraisal of amendment' and causes highly specific agents (i.e. those with a narrow breadth of expertise) to overrate the technological adjustments proposed by a collaborator. Harking back to our story on the development of the sector over time, we see that this ill-appraisal exists due to a coinciding of development of the technology frontier and the collaboration propensity. By the time the market has matured, the strategies that apparently survived bring about a collaboration propensity that neatly reflects the actual gain in fitness expected from collaboration.

As far as *appropriability* (and its interaction with *complexity*) is concerned, we have seen that the effect of patent duration on the collaboration propensity suggest that there is no spillover; patenting does not stimulate collaboration propensity. On the contrary, we saw that the patent duration amplifies an early mover advantage and thereby even stimulates working solo!
We have subsequently investigated the effect of appropriability on the relationship of externalities with collaboration propensity and discovered interesting phenomena at stake. We saw that there are two phenomena actually striving for precedence in case of externalities. Firstly, we have seen that agents can rely on something we have called 'externality-opportunism', i.e. agents can partially rely on the influx of reverse engineered technologies. Secondly, we have seen that the collaboration strategy reflects the extent to which collaboration would boost the resilience. We argued that collaboration both contributes to exploitation of the head start and patent circumvention. We also argued that collaboration for resilience is predominantly interesting if appropriability is sufficiently high.
We saw that the evolutionary preference for a particular collaboration strategy is less clear on the long term, especially if there is high appropriability. Externalities make the causal relationship between innovation qualities (and hence collaboration strategy) and survival weaker. Coincidence and mere chance also play a considerable role in the survival of agents, especially if appropriability is high.

As far as *level of competition* and its interaction with *complexity* is concerned, we have seen that collaboration propensity typically increases strongly if competition is severely fierce. We argued that in the absence of spillover, the complementary control provided by collaboration increases the probability of finding top-fit technology, which is needed desperately to resist competition. We see that this behavioral already emerges strongly in the onset phase, but there is an even stronger inclination toward collaboration in the mature phase.

Chapter 7

Conclusions and suggestions

We started this research with the question whether R&D collaboration propensity increases with the technological complexity. With a preference for conducting experimental research, we decided at the outset that we would resort to Evolutionary Economics and more specifically to Neo-Schumpeterian models to address our research question. As Neo-Schumpeterian models have an R&D model (strategic and/ or operational) at their very core, we also had to pick such a model. Following the wave of enthusiasm over the potencies of modeling R&D as hill-climbing search on an NK landscape, we explicitly agreed upon adopting the NK landscape. From some preliminary excursive experiments with the NK landscape, we had some doubts about its validity and decided to simply evaluate the adequacy of the NK landscape and the main research question all in once.

With the presumptions of the Neo-Schumpeterian theory and the strong emphasis on uncertainty in innovation outcome in mind, we decided to adopt the Transaction Cost Economics theory for its conciseness and conclusiveness and the fact that uncertainty is an integral part of the theory. We ~~however decided to refine the uncertainty concept and to thereby be able to integrate mediating~~ factors that emerged from recent empirical findings and adjacent Strategic Management theories.

We subsequently conducted a survey of the Neo-Schumpeterian models of R&D collaboration, and hereby distinguished both fundamental models as well as fully-fledged, conceptually rich models. We also conducted a survey of technology landscape models to look for a suitable candidate to study R&D collaboration. In the end, we were -in line with our initial conceptions- strongly inclined toward the more fundamental NK landscape as it would allow us to immediately operationalize the factors in our conceptual model, the adorned TCE model. We also shortly introduced the reader to the methodology of simulation model design. This functioned as a guideline for our design practices and helped us understanding the interplay of the validity of our operationalizations, conceptual model and research findings.

Subsequently, we presented our operationalization of our conceptual model and formulated the operational hypotheses. Behind the scenes, we in the meanwhile implemented the operational model, scanned the parameter landscape and picked suitable parameters to finally generate the results presented in chapter 6. The obtained results of the simulation were found to (partially) contradict our operational hypotheses at first sight, but rather than mere verbal inference, we showed that exploration of properties of core modules of our simulation model indeed introduces phenomena that -when expressed in mathematical terms- explain considerable variance in a regression model.

In this chapter, we will recapitulate our conclusions on the operational hypotheses and interpret these within the TCE theory realm. We will first briefly evaluate the way we came to our current simulation model design and to sketch the difficulties we encountered. This also gives some momentum to our conclusions concerning the use of the NK landscape and is an indication of the importance of diffusing the results. We will then shortly evaluate the role of the various components in our operational model in our simulation results and pinpoint were our operational models has shortcomings. Taking into account the operational shortcomings and hence the (slightly) limited conclusions on the relationships in the TCE framework, we then sum our current understanding of R&D collaboration under technological complexity and shortly reformulate the adorned TCE framework buttressed with our operational level understanding of the matter. We will then formulate suggestions for further research, thereby (provocatively) call upon the research community to put particular issues on the scientific research agenda and, finally, provide some tips for fellow-students (and scholars) on the issues to bear in mind during design of an operational (Neo-Schumpeterian) model.

7.1 Evaluation of simulation model design, operationalization and quantification

The first model we designed was comprehensive and had agents engage in multiple, multi-period projects with collaborators they picked using a multidimensional criterion and hereby investing credits in both search and research according to an investment heuristic. Due to the large number of dimensions, the evolutionary forces were only weak and the collaboration strategy was only poorly trained which resulted in considerable variance in the output. We hence decided to simplify the collaboration selection heuristics.
That second model produced results that would contradict the central hypothesis even after extensive experimentation with parameters. In line with the simulation design methodology provided in chapter 4, we had to work our way upward in finding the flaws in our work and it was most likely there were either bugs or imperfections in the code or design defects. Code inspection, white-box and degeneracy testing did not reveal programming errors, so we had to look for the problem one step higher in the model design ladder. We returned to the drawing board to have a look at the operational model. We reasoned that part of the problem was that in case of low complexity, projects take longer and hence consume more credits for search at the expense of credits for research. We felt this R&D conception both counterintuitive and considered it distorting our collaboration propensity output measures.
As such, we further reduced the model, while, at that time, we were still convinced that our simulation model would eventually confirm the central hypothesis. First, we took out the innovation costs to circumvent that complexity correlates negatively with research costs (more inventions) and, as such, only left fixed invention costs and no innovation costs. We furthermore reduced the R&D conception from an agent having multiple projects, each running for several periods to an agent having exactly one project that it finishes that same period. We thus limited the effect of complexity to the fitness of the technology discovered and removed the effect of complexity on issues like project running time and search costs. In this same model, we removed the transferring of technologies between agents (spillover) as the reduction in costs due to spillover no longer played a role as there are no search costs. Its effect moreover was rather insignificant anyway, but we will come back to that later. This technology instance transfer furthermore made simulation very slow and memory consumption considerable.

After all this work, even this last, concise model again produced results that contradict the central hypothesis, and again the parameter quantification and operationalization as well as the design were heavily scrutinized. After finding no flaws, we started to fathom the properties of the core components of our model (e.g. technology landscape search, matching, patenting) and the way these properties affect the emerging results. From this we gained enough confidence in the implementation validity and the obtained results to present them in chapter 6. As we have seen, especially the fundamental properties of landscape search, our matching algorithm and absence of market and proper unilateral governance determine the actual outcome. In the light of these properties of (the core of) our simulation model, it is -in retrospect- not even hard to grasp why collaboration does decrease with complexity!

In the light of the design methodology proposed in chapter 4, we see that the operational validity of our model is limited as far as the operationalization of complexity goes . By extensive experimentation, bug hunts, degeneracy testing and the like, we have assured implementation validity, so the lack of internal validity (i.e. the fact that our model is inadequate in reflecting the properties of complexity) is immediately related to poor operational validity of our operationalization of complexity. Due to our choice for this particular technology landscape search model, we have introduced an artifact in the search outcome (decreasing technology performance/ fitness and innovation performance augmentation for increasing complexity) and, thereby, in the emerging strategies. This, in the end, results in a discrepancy in the outcomes as predicted by our TCE model and the outcomes

as simulated.
In the next section, we will moreover elaborate that, since spillover is absent in our model, the role of appropriability is also limited. We will see that we hence sit on one side of the continuum as far as the role of the level of competition goes. We will also go into the results of absence of a proper operationalization of the R&D strategy 'market governance' and -perhaps more concerning- 'unilateral governance'. However, taking these limitations into account (i.e. not comparing emerging properties across different levels of complexity, bearing in mind that there is no non-appropriable spillover and bearing in mind that part of the propensity we measure stems from 'concealed buying/ internalization'), our simulation results actually quite neatly correspond to theoretical framework! So, although we have to acknowledge that the operationalization is flawed, taking into account the limitations in interpreting the results within the realm of the adorned TCE framework, we are inclined to conclude that there still is considerable internal validity. In chapter 7.4, we will see that our understanding of R&D collaboration and the role of complexity therein has deepened in that it can be provided with an integrated operational explanation with fundamental mechanism that are at work.

7.2 Conclusions on simulation results and implications for theory

In this section, we will recapitulate the findings presented in chapter 6 and interpret them within the realm of our adorned TCE framework. We know from chapter 4 that simulation as research tool has one to be careful in interpreting the simulation results in terms of the theory from which it is derived. Operational validity might be impaired by design choices. We have just seen in section 7.1, that in our attempt to eradicate an unexplained phenomenon, we have drastically reduced our operational model. Although we have thereby assured implementation validity, we made our operational model less descriptive and still failed to get out this (then still) unexplained phenomenon. Our design choices in operationalizing the TCE factors and operational R&D seem to have impaired the operational validity and thereby the internal validity. It however is not so dramatic as it may sound. In this chapter, we will see that we are well capable of explaining the rationales behind the phenomena observed in our results using the TCE terminology! So, our TCE model is robust in explaining the behavior after we have applied the restrictions emanating from the operational shortcomings! It is not so our TCE framework has obvious gaps in explaining the collaboration propensity!

Here, we will simply interpret our findings factor-by-factor, thereby relating our expectation formulated in subsection 2.3.1 and operationally formalized in hypotheses in section 5.7 to our findings in chapter 6, hereby using the operational definitions provided in chapter 5 and the properties of those operationalizations observed in the model as well as the results chapter.
In addressing differences in high- and non-high-tech sectors, we, as explained in subsection 2.3.2, aimed for a two-dimensional analysis of each factor in conjunction with complexity (which we in fact did in chapter 6). In subsection 7.2.5, we will evaluate the predicted collaboration propensity in relation to assessed levels of each of the factors (and the development of the propensity for changes in the factor levels).
Finally, in subsection 7.2.6, we will provide a concise summation of the findings. We hereby also explicitly emphasize the role of the operational shortcomings of our model as we will take them as a starting point for our elaborate analysis in section 7.3 of what now is wrong exactly with our operationalization and what can be improved.

We will not extent our discussion to the traditional TCE, but rather stick to the wording in our more disaggregate, adorned TCE model terminology which by and large coincides with the terms ordinarily used in business economics. We take this as a hint that we do not (or: do no longer) need to translate the exerted forces into the traditional TCE terminology to be able to pinpoint its workings. This appears to be virtue of our disaggregation of this framework and adornment with Strategic Management terms.

7.2.1 Complexity

We will first recapitulate the findings on the TCE factor complexity. We have to be careful in interpreting the findings as the simulation results are distorted by the model artifact complexity catastrophe.

The TCE model established in section 2.3.1 is constructed around the idea that complexity induces technological uncertainty, which in turn has firms collaborate. We have designed an operational model that enabled operationalization of the TCE factors, amongst which complexity, and as such allowed us to experimentally investigate the main hypothesis. Only during simulation and redesign, we discovered that some features of the model not only limit the external validity, but even violate stylized facts. As we just saw in section 7.1, we went through extensive efforts to get our model to reproduce the operationalization of the central hypothesis $K \xrightarrow{+} \Lambda$, i.e. the collaboration propensity increases due to increase of complexity, but we did not succeed!
In the concise, condensed model we currently use, we have found the fundamental cause of the fact that the collaboration propensity indeed does decline when complexity increases. We have seen that especially the complexity catastrophe determines the level of collaboration as a rise in complexity has the fitness of optima regress to the mean. Hereby, the innovation performance augmentation achievable by collaborating rather than working solo in fact decreases with an increase in complexity. As fitness is positively and directly related to payoff, it becomes harder to financially justify involving a collaborator if complexity increases.
This complexity catastrophe is a property of the NK landscape that forms the basis of our technology landscape search model. This reduction in achievable innovation augmentation (by collaborating rather than working solo) for increasing complexity hence is an artifact of our model. We will elaborate on the operational shortcomings of our technology landscape model in subsection 7.3.1. So, rather than allowing us to operationalize the non-decomposability of technological complexity and thereby making the exact combination of technological to realize properly performing technology more delicate if complexity increases, our technology landscape makes the exact combination of technological elements less of relevance and thereby performance less sensitive for technological changes when complexity increases!

Regretfully, we cannot conclude more than this. We can however use the insights gained by working with the technology landscape in refining our expectations on the operational benefits of collaborating. We claim that the motivation of firms to engage in a technology alliance stems from: (a) the preemptive signaling of incompatibilities by the collaborator (without which the firm would perhaps end up with completely dysfunctional technology) due to the non-decomposability and (b) the synergistic advantages enjoyed by being able to escape basins of attraction in which the firms would remain stuck otherwise. Such motives play a strong role when both the technological intricacy is high and the technology is yet premature, i.e. if the 'relevant' complexity is high (the knowledge is highly specific and not publicly available and there are no standards and interface specifications yet).
If we now look at the results for the onset phase, we see that these benefits are certainly not that apparent. In that case, there are many technological opportunities and both collaboration as well as working solo produces technologies that still have a fair chance of entering the market. It requires only a few R&D projects to come up with products eligible to enter. As there furthermore still is a fair probability that developed products fall within the mid- or top-range, this implies there is considerable chance on a fair return and being able to build some (modest) resilience for market shocks. This effect is furthermore amplified by appropriability, as we can tell from the 'early mover

advantage' effect.
We are inclined to conclude that collaboration to overcome technological uncertainty (and, as hinted, also non-decomposability as a prominent factor) occurs when the sector is maturing and technological opportunities are dwindling fast.
We came to yet another insight that we cannot immediately pinpoint in the data. We stressed that we cannot disentangle the effect of the decreasing achievable innovation performance augmentation (caused by the complexity catastrophe) and the 'concealed buying' of complementary components that occurs particularly for low levels of complexity. If we extend this thought and revert to the adorned TCE framework, we claim that, for low levels of complexity, this concealed buying takes the ordinary form of outsourcing or buying. We claim that the general drift is that there is no to little collaboration due to absence of synergistic innovation performance augmentation (which is contrasting the measured collaboration propensity!). Hybrid rather than market governance would only be an additional risk of adherent spillover, while such risks can be detrimental in an industry with low concentration. In the simulation model, however, if complexity is low, the expected outsourcing and purchasing on the technology component supplier market takes the form of 'concealed buying', hereby increasing the measured collaboration propensity. This 'concealed buying' of course is particularly strong when the competitive pressure is high (e.g. when the technology frontier is mature, when competition is fierce) as innovation performance is crucial.
~~Again within the realm of the adorned TCE framework, we claim that the general drift~~ is that, if complexity is high, that the collaboration propensity is high. Working together allows the parties to reap the synergistic innovation performance augmentations which actually are there. If appropriability however is low, firms are inclined to internalize development. If complexity is low, firms are inclined to outsource development or purchase complementary components. In the simulation model, if the complexity is high, the complexity catastrophe of course squeezes the synergistic innovation performance augmentation and thereby suppressed the inclination to collaborate. The governance form 'unilateral governance' (internalization) is unoperationalized, but this would reflect in the collaboration propensity. If complexity is low, agents would rely on 'market governance', which is, due to absence of an operationalization, reflects in the 'concealed buying' occurring.

So, since our operationalization of complexity (as introduced by the landscape search model) is deficient, we can, regretfully, conclude little on the effect of complexity on collaboration propensity directly from our results. However, since we have fathomed the fundamental mechanisms at work in our simulation, we came to interesting insights and inferences about operational causes for collaboration and working together. For high complexity, firms look for synergy in innovation. For low complexity, firms work solo and simply purchase complementary components. Clearly, we need to look for an alternative landscape definition and add operational R&D action options operationalizing market and unilateral governance.

7.2.2 Complementarity

We will first shortly recap the TCE factor complementary, its effect on collaboration propensity and our operationalization of that relationship. We will then interpret the simulation results for complementarity found in section 6.3 in which we controlled for breadth of expertise and registered the effect on collaboration propensity. We will also stipulate the findings for different phases in our simulation (and hence the different stages of development of strategies employed). We will only shortly evaluate the shortcomings of our operational definition for complementarity (e.g. caused by insufficient accounting for the human capability to engineer technology in our conception of innovation) and not evaluate the the peculiarities of the current operationalization (e.g. interdependency with complexity) as we will do that in section 7.3 in detail.

In the TCE model, it is stated that the complementarity of a sector determines the propensity to collaborate. If complementarity is high, the achievable increase in innovation performance by collaboration is high. At a disaggregate level, we postulated the hypothesis that the compound effect of contribution in scope of control over technological elements and the additional fitness assessment qualities (i.e. the benefits of joining the fields of expertise) on collaboration propensity displays an inverted-U form. Operationally, this boils down to the hypothesis that, given the complexity K, agents work together most if their breadth of expertise E is intermediate and less if the breadth of expertise is either higher or lower, i.e. $E \xrightarrow{\cap} \Lambda$.

In appendix B, we have seen that the fundamental degeneracy tests confirm this parabolic nature. In section 6.3, we have seen that our model does confirm the parabolic nature, that is, by the time the simulation run finds itself in the mature phase, when the technology frontier has progressed and the shake-out of strategies has occurred. The relationship $E \xrightarrow{\cap} \Lambda$ emerges due to the evolutionary importance of the *actual* innovation performance augmentation established by collaboration, especially under a tight market regime.
Recall that, in the mature phase, the customer preference dimension of market uncertainty is no longer at stake; the technology frontier has progressed and the consumers typically want those quality products. Overcoming the technological uncertainty and producing top-fit technology however becomes more crucial in survival. Since the firm strategy has also gradually developed due to propagation of the strategy, we expect that there is a structural tendency toward collaboration.
The interpretation of the finding that the 'actual innovation performance augmentation' explains the collaboration propensity is straightforward. Firms seek contribution only if the reduction in technological uncertainty, the increase in innovation performance and hence the additional payoff is sufficiently high to justify sharing the needed payoff. The firms that have survived so far follow strategies that take this sufficiently into account as firms that did not do so were dynamically inefficient and have already gone bankrupt. The surviving firms hence found the balance between collaborating to overcome technological uncertainty in certain cases, and, in the meanwhile, hereby preventing overrating collaboration as it might dig in on the desperately needed payoff.
It must be said that due to absence of spillover, let alone *adherent* spillover, the collaboration propensity only reflects the static innovation performance increase and the way that this affects the chances of survival, but not the increase in dynamic efficiency that firms accrue by learning from collaborators. Our interpretation hence is restricted to translating the operational benefits in terms of innovation performance increases into the realm of the TCE framework.
If the complementarity is low, there might be three causes. Firstly, firms either are relatively specialized while facing a large-scale technology. Secondly, the components produced by firms hardly are interconnected (making buying-and-applying of components or outsourcing development of complementary components the way to go, in reality). Thirdly, the additional control contributed by the potential partner is too low. In all cases, the reduction in technological uncertainty and synergistic operational efficiencies by collaborating are modest. Although it still is true that the innovation performance is better for the collective than for the individual, the slight technological improvements are *so* modest that the additional returns from R&D do not outweigh having to share them.
If the complementarity in a sector is high, the firms in the technology alliance bring in capabilities of complementary disciplines and can as such together cover most of the components that need to be produced, and, furthermore, there is considerable interconnectivity of the parts and components of the technology. Clearly, collaboration allows overriding (implicit) standards and firms can reap synergistic advantages by pursuing interesting technological opportunities that were previously unavailable as they would yield incompatibilities with complementary components not within control. Due to the wide range of disciplines thus merged and the fact that a large part of the components are under control allows the alliance to achieve an innovation performance that is close to what is maximally possible. Surely, the attractiveness of collaboration is then at its peak and indeed we measure a peak in collaboration propensity.

The situation is completely different in case the simulation is in the onset phase as the technol-

ogy frontier is still strongly developing and the limited exertion of evolutionary forces has not yet brought about a shake-out of strategies. Agents that suffer from ill-appraisal (i.e. in case that agents are highly specialized) are not yet punished as collaboration does still yield (slightly) fitter technologies considerably more often. We find that $E \bar{\rightarrow} \Lambda$ and hence believe that this stems from the omnipresence of insufficiently punished and hence still surviving strategies which are guided by ill-appraisal of the proposal of the potential collaboration partner. It is noted that if complexity is high and firms are highly specialized, these firms still suffer some ill-appraisal even if the technology frontier is mature. We expect this ill-appraisal to be eradicated eventually.
If we now interpret these simulation results in the realm of the TCE framework, we are inclined to attribute continued existence of firms suffering from ill-appraisal to the presence of ample technological opportunities (after all, the technology frontier is premature in the onset phase), the conditions are mild for firms, regardless of their innovation performance and dynamic efficiency. Firms with relatively (and rationally) inferior strategies are yet insufficiently punished and due to the presence of these inferior firms it hence happens that collaboration propensity is higher than justifiable for when looking at the achievable innovation performance of more over less collaborative firms. We argued that due to this lenient market regime, the underlying, yet ill-conditioned collaboration *beliefs* dictate the propensity rather than the actual and factual collaboration benefit. As the appraisal qualities of firms become worse if they become more specialized, their range of valuations of suggested technological adjustments becomes wider. This causes firms -even given the same decision criteria- to agree more often to collaborate. Under this yet lenient market regime, we indeed measure more collaboration if firms are more specialized.

The Elektroson anecdote in 1.1 proves a good illustration of how things go. In the modestly mature Internet sector, all kinds of ideas flourished, making the R&D department explore exotic technologies and follow unusual technological avenues. In line with what we argue, this is also likely to make firms eager to engage in technological alliances to bridge technological gaps, to reap complementarities and to thereby strive for establishment of dominant designs. Due to ill-appraisal of the true value of proposals and amendments, partners might be lured into collaboration while the actual profitability of the innovation under development is uncertain. As in the Elektroson case, both Netscape and Elektroson were convinced they were heading for -at least- a competitive advantage but covertly even dreamed of world domination. The 'webgrabbing' functionality however posed R&D for unforeseen highly challenging technical issues and the developments in the product market and in auxiliary technologies rendered the innovation totally unattractive in the end.

Let us shortly sum the most important conclusions. Firstly, by the time the simulation is in the mature phase, the strategies that have survived are conditioned by and large to have the collaboration propensity reflect the marginal innovation performance increase possible under those conditions (i.e. levels of complexity and complementarity). Secondly, we see that, in the onset phase, the strategies have yet been insufficiently punished for their ill-appraisal due to ample technological opportunities. Due to the resulting overrating of collaboration, the measured collaboration propensity is higher than can be justified for from the performance augmentation achieved.

7.2.3 Appropriability

We will first shortly reiterate the TCE factor appropriability, the effect of appropriability on collaboration propensity (via the effect on the use of spillover) and the operationalization of that relationship. We then interpret the simulation results and hark back to the properties of spillover in our operational model to explain these results. Due to the nature of those properties, we have also paid attention to the effect of externalities. We will evaluate the simulation results on the intermediating role of appropriability on the relationship between externalities and collaboration propensity. We will then revert to the TCE framework and evaluate what we have found.

In the exposition of the TCE model, it was argued that if appropriability increases, the governance forms shift to become more external. In case of commonly internalized R&D activities, hybrid governance forms become more likely. We formulated an operational hypothesis on this in section 5.7, stating that if agents are able to enjoy the 'patent owner share' of returns from R&D for a longer period of time (increasing ω), that agents would be inclined to collaborate more (increasing ω), i.e. $\omega \xrightarrow{+} \Lambda$. The underlying argument is that appropriability boosts the marginal increase in total payoff (i.e. due to collaborating rather than working solo) by prolonging the period in which monopolistic rents can be enjoyed, and furthermore, by diminishing the negative effects of outgoing spillover and resulting externalities. Although other agents (not necessarily the collaboration partner) might catch up quickly, they will now no longer be able to immediately enjoy the same payoff as the inventor(s). The receiver of the spillover will not be able (or, at least, less able) to put the received knowledge to opportunistic use. Appropriability would thus increase the advantages and decrease the disadvantages of collaboration.

We however already observed in section 5.4.3 that the effective spillover is limited. Due to the instance nature of our technology landscape as opposed to a 'capability' technology landscape, there is no adherent spillover of innovation engineering knowledge and the consequences of leaking a single instance are virtually insignificant. Since there is no substantial spillover, the effect of appropriability on collaboration propensity cannot be attributed to the fact that appropriation instruments protect the originator from opportunistic use of that spillover by the receiver. We see this confirmed by the results presented in section 6.4: there are no positive effects of appropriability (ω) on collaboration propensity. On the contrary, we concluded that there is an 'early mover advantage' that allows initial agents and early entrants to build up resilience, which especially pays off if they work solo, and that this strategy is more effective if appropriability increases! Late entrants fail to get sufficient market power, especially if complexity is high, as they fail to get (unprotected) top-fit technology and either receive too little payoff to cover the fixed costs (and hence are forced into demise) or can only gather a small buffer making them vulnerable for market shocks.

We however also reasoned that the detrimental effects of reverse engineering or rather existence of externalities (ρ) are largely neutralized by means to appropriate; even if other agents reverse engineer technologies on the market, the original developer still enjoys monopolistic rents. In section 6.4, we explored the effect of appropriability in the presence of externalities and discovered that appropriability does bring about an increase in collaboration propensity.

Collaboration helps 'exploiting the head start'. The probability of improving a proven concept (the top-fit technology already on the market that is reverse engineered) into another top-fit technology is larger than starting anew and ending up in another top-fit technology. It is relatively easy (and cheap) to just (try to) improve that technology. Not only does involving a collaborator then boost innovation performance, it also increases the chance of ending up with technology that does not infringe the existing patent on that particular reverse engineered technology (but also the existing patents on technologies that also were directly derived from that particular technology). If patent running time becomes longer, it becomes increasingly more crucial to survival not to only avoid infringing patents (as the expected remaining running time of the patent until expiration increases), but also to get one of those patents on top-fit technology. Firms collaborate to circumvent patents on the reverse engineered technology and to rather fetch one themselves, especially if complexity is moderate to high and, moreover, the longer the patent running time, the more urgent it becomes. As this urge is felt throughout the population, firms make it more difficult for one another to survive and in the end intensify this process for themselves!

If the sector suffers from high levels of externalities, e.g. if the technology can be reverse engineered easily as e.g. in the automobile industry, there also are firms that mainly rely on influx of the knowledge obtained by reverse engineering and simply follow by producing similar products. As soon as appropriability of technology increases, this 'externality opportunism' strategy no longer works since simply imitating would infringe patents. The patent owners furthermore can really enjoy the

returns from their innovation efforts and hence surely have a financial resilience over followers. Coincidentally, exploitation of the head start and patent 'circumvention' effects are more sought after and we indeed observe that firms start to collaborate more.
The effect of appropriability on the discouraging of a 'following' or externality opportunism strategy is so effective, that it is clearly measurable even during the onset phase despite that the results are distorted by inferior strategies. Clearly, the probability of infringing a patent of a reverse engineered technology in a mature phase is higher than infringing a patent of a reverse engineered technology in the onset phase, as technological opportunities are somewhat better. The necessity to circumvent patents is therefore somewhat less, but since the market is still shifting rapidly, having top-technology allows one to longer enjoy the benefits of the developed technology (as such technology is not so quickly degraded).

Let us recap the conclusions. Spillover is absent and rather than that appropriability protects innovators from opportunistic use of spillover and thereby stimulates collaboration, early movers build up resilience by working alone. We therefore also focus on externalities. We saw that, when externalities are present, appropriability invokes collaboration. First of all, appropriability makes it extra worth while getting a top-fit technology and clearly even worth collaborating to achieve that, especially since collaboration effectively exploits the head start of reverse engineering. Second of all, when facing likely infringement of patents on technology being reverse engineered, collaboration increases the probability to circumvent them. Third of all, with a rise in appropriability, firms can no longer rely on influx of technological knowledge by means of externality-opportunism, but must have a decent innovation performance themselves. Collaboration aids in that. Fourth of all, in the onset phase, the technological opportunities are best exploited by assuring that you can enjoy the top position as long as possible before the technology is degraded and tipped off the market.

7.2.4 Level of competition

We will first recap on the effect of the level of competition in the sector in determining the collaboration propensity. We will reformulate the operational hypothesis and subsequently evaluate the simulation results. We will see that non-appropriable spillover strongly mediates the presupposed effect of competition.

The TCE model provided in section 2.3.1 resolves the ambiguity in claims about the effect of competition. On the one hand, some authors argued that competition makes firms wary to collaborate as spillovers are likely to be detrimental to relative performance and as such dynamic efficiency, while other authors argued that competition would necessitate dynamic efficiency and as such force firms to seek complementary knowledge. We signaled that we should especially be looking at the level of non-appropriable spillover to explain where a sector finds itself on the continuum. We argue that firms are inclined to collaborate if the innovation performance augmentation by collaboration outweighs the disadvantages of outgoing non-appropriable spillover.
Under the precondition that there is a normal level of non-appropriable spillover, we argued that if the competition increases, that agent are less likely to collaborate. We operationalized this as the hypothesis that if the scarcity of credits for payoff (the demand size D) increases, agents are less willing to share the technological knowledge and risk (opportunistic) use of spillover at own expense and hence are less likely to collaborate, i.e. $D \xrightarrow{+} \Lambda$. Recall that we discovered the opposite: if there is a great scarcity of credits being disbursed periodically, agents are inclined to collaborate more to get at least a share of those credits!

We argue that if firms face fierce competition, their market share is in expectation small and it is difficult to finance R&D from returns of previously developed products. As there is a real frenzy of firms developing products to cut themselves some slack and gain some resilience for market shocks, all firms are forced to increase the probability of developing a top-fit product. If only a couple of firms start to R&D products together, their innovation performance is (relatively) higher and they have a bigger chance of coming up with top-fit products. Since other firms that work solo are unlikely to find a top-fit technology in the few attempts they have and hence receive only very little payoff, these 'collaborative' firms force those 'solo-minded' firms into demise. Please realize that if the chance of survival increases, it becomes more likely their collaboration strategy is propagated. So, it really is a matter of being lucky to obtain a top-fit product and, since this chance increases by involving a collaborator, the collaboration propensity develops to become relatively high in the end.

We however have to place a remark here. Since spillover is insignificant, firms do enjoy the benefits of complementary knowledge and only have to share the payoff without suffering the detrimental effects of spillover. If we hark back to the exposition of our TCE model, we see that we simply sit on one side of the continuum; the side where non-appropriable spillover is absent, i.e. where all spillover is perfectly appropriable or spillover is completely absent.

If, on the other hand, the level of competition is low, then the innovation performance is relatively unimportant for survival. In that case, complementary knowledge is unimportant and the solo-minded early movers might even build up more capital stock than collaborative firms. So, either the strategy population is a mix of solo and collaborative strategies or might even tip to solo R&D collaboration strategies.

Let us shortly sum the (modest) conclusions. We see that due to absence of spillover, the consideration of whether or not to collaborate primarily focuses on the increase in innovation performance that is brought about by collaboration. If payoff quickly drops with market shocks and these market shocks occur frequently, collaboration is the best way to prevent producing products that degrade quickly and generally generate little payoff.

7.2.5 Sectoral differences

In subsection 2.3.2, we explained that we would not 'reenact' the (stylizations of) high- and non-high-tech sectors by configuring the operationalizations of the various TCE factors for simulation, but rather preferred to pinpoint the role of each of the factors in isolation in conjunction with technological complexity in high-tech and non-high-tech sectors. In subsection 2.3.2, we have provided assessment of the likely combinations of complexity with either complementarity, appropriability and the level of competition. We argued that complexity and complementarity are most likely to be both high or both low. We argued that in case of high (low) complexity, we expect (low) high inherent appropriability and (low) high levels of competition. We will here evaluate the collaboration propensity in case these combinations occur. In subsection 2.3.2, we also assessed the effect of the factors if we fix the level of complexity on the collaboration propensity. We will also shortly recap on our findings with regard to these presupposed effects. From the previous subsections we know what the operational flaws in our model are and what the emanating restrictions to our adorned TCE framework are. We have to be careful with interpreting findings across levels of complexity, have to be aware that we are on an extreme side of the spillover continuum when considering the role of complementarity and appropriability and, finally, we have to be aware that part of the collaboration propensity we measured is a 'concealed buying/ internalization' due to absence of operationalizations for those governance forms. We can use these understandings here to refine our interpretation of the findings.

We will now first discuss a vexing issue with our factor complexity and our association of high- and non-high-tech sectors with high respectively low levels of complexity. We will then consecutively discuss our findings for the level of complementarity, appropriability and finally the level of competition.

Let us first shortly discuss our association of complexity with technological intensity as we have

introduced in subsection 2.3.2. We signaled that non-high-tech sectors generally are more mature, that the paradigms are more clear and that the technologies are more standardized. This implies that the technological complexity is generally lower as the number of interdependencies between modules and disciplines is lower. We argued that if we focus on the dimensions decomposability and maturation/ specificity of the sector, we can bijectively associate a sector being high-tech or non-high-tech with the sector having high versus non-high technological complexity.
As discussed in subsection 5.2.4, we do not operationalize these two dimensions explicitly. As far as the dimension maturation/ specificity of the technology principal to the sector goes, we get away with it quite nicely. As we will discuss in subsection 7.3.3 in more detail, we indeed do not incorporate processes of standardization, modularization and aggregation of the technology landscape, nor specialization/ integration affecting the industry organisation/ segmentation, so indeed maturation/ specificity of technology does not come about endogenously. However, we can associate intricacy K with the level of *relevant* complexity by acknowledging that only the interdependencies that need to be taken into consideration given the reduction in complexity by standardization et cetera are relevant in (incremental) innovation.
If a similar indirect association holds for intricacy with non-decomposability, we are able to say that we are looking at a high- or non-high-tech sector simply by picking a different level of intricacy. Regretfully, we are not so lucky this time. When we discovered the manifestation of the complexity ~~catastrophe, we realized that fitness does not reflect technological performance as we expected~~ it, and that we thereby lost the relationship of intricacy, via the performance measure, on decomposability (we will discuss this in great detail in subsection 7.3.1).
Due to the hampered association with the level of decomposability, a change in intricacy is not completely a change in complexity and certainly not in technological intensity. As a consequence, we have to be careful with cross-comparing the simulation results for our stylizations of the high-tech and the non-high-tech sectors and interpreting them within the realm of the TCE framework. For instance, based on theoretic arguments, we expect collaboration for complementary knowledge (to overcome non-decomposability of such complex technology) to occur especially in high-tech sectors, but we have to be careful with comparing the level of collaboration obtained in simulations for the stylizations of the high-tech and non-high-tech sectors. Rather than seeing a 'collapse' of the technological performance distribution to zero percent due to the non-decomposability of complex technology, which we expect to observe for a high-tech sector vis-à-vis the distribution for a non-high-tech sector, we see a regression to the mean of fifty percent of the fitness which clearly does not reflect non-decomposability (we will elaborate on this in subsection 7.3.1). Since the actual achievable innovation performance augmentation becomes less rather than more significant, the collaboration propensity is lower than expected.
Regardless of this issue, we can still evaluate the intermediating effect of the other factors for fixed levels of complexity, and cross-compare the emerging propensity as long as we bear in mind that part of the difference in collaboration propensity is to be attributed to the consequences of this poor operationalization of non-decomposability.

In subsection 2.3.2, we argued that low (high) levels of complexity go hand in hand with low (high) levels of complementarity. Recall that these factors are not completely perpendicular as there is some interdependency through the dimension of technological intricacy that these concepts share. In high-tech sectors, we argued that there is high complexity and high complementarity, so firms are relatively specialized while there is considerable intricacy. Based on theoretic arguments, we expect considerable collaboration propensity as working together augments the innovation performance synergistically since firms can pinpoint imminent incompatibilities and preemptively suggest alternative solutions.
In our simulation results, however, we expect to find low levels of collaboration propensity, since the complexity catastrophe strongly manifests itself in case of high complexity. The complexity catas-

trophe reduces the magnitude of those expected synergies by squeezing the achievable performance increases. Quite to our surprise we find a collaboration propensity that is higher than expected, which is attributed to the manifestation of the ill-appraisal effect (even if the technology frontier is mature and the R&D strategies conditioned). This ill-appraisal effect is after all strongly present if firms are specialized and if intricacy is high. The expectation however is that after a long while, the collaboration propensity will properly reflect the achievable innovation performance augmentation (see appendix B).

In non-high-tech sectors, we argued that there is low complexity and low complementarity, so firms have a relatively broad scope of activities, but there is moderate to low (relevant) intricacy. In section 2.3.2, we argued that complementary knowledge is of little value and that we hence expect low collaboration propensity. We see in our simulation results that there initially is (i.e. in the onset phase) a moderate level of collaboration, which is argued to stem from ill-appraisal. Over time, the achievable innovation performance improvement -that is, by the way, largely non-synergistic and primarily a 'concealed buying' of complementary components- reflects in the collaboration propensity. Be aware that in the case of low complexity, the complexity catastrophe is only weakly present.

If we fix the level of complexity, we see that an increase in complementarity (i.e. more or less $|E| \rightarrow N/2$), the collaboration propensity increases, in line with our theories, but only for low to moderate complexity. For high complexity, this is only the case if all-rounder firms become somewhat more specialized ($|E| \downarrow N/2$). The change in collaboration propensity caused by highly specialized firms becoming less specialized ($|E| \uparrow N/2$) is even in the mature phase still somewhat distorted by the over-appreciation for collaboration caused by the ill-appraisal effect.

With regard to the effect of appropriability in high-tech and non-high-tech sectors, we argued in subsection 2.3.2 that -presuming that the lion-share of spillover and externalities are non-adherent- that appropriation is expected to be more effective but also to be more required in non-high-tech sectors (so we expect high inherent appropriability and also intensive use of appropriation instruments). On the other hand, we argued that appropriability has a weak effect on collaboration propensity if complexity is high as it is supposedly easy to circumvent patents of complex technology and technology is hence more difficult to protect anyway.

However, the effect of appropriability on collaboration propensity is thwarted by the absence of spillover. We cannot tell from our simulation results whether opportunistic use of spillover in collaboration occurs more in high-tech or non-high-tech sectors. We however discovered that appropriability amplifies the early mover advantages for soloists, especially in high-tech sectors. If we look at spillover as sec non-adherent recipes for technological components that are conveyed upon collaboration, opportunism is less effective in high-tech sectors as the intricacy and high number of interdependencies make blunt copying of components interfere with proper functioning of other components.

Just as elsewhere, we look at the effect of appropriation if we introduce externalities in conjunction with complexity. If we look at the findings, we see that in case of non-high-tech sectors (low complexity and high levels of appropriability), there is a lot of collaboration, while in case of high-tech sectors (high complexity and low levels of appropriability), there is a lot less collaboration. This is the case in both the onset and the mature phase. If we look at the fundamental causes, we see that collaboration to circumvent patents is very effective if the complexity is low and of course also desperately needed if appropriability is high. We see that the role of complexity in the effectiveness of appropriation seems to be different then conceived in theory and we claim that -despite our flawed technology landscape search model- we see support for our findings. Our results and our inferences thereof indicate that by the nature of the technology landscape search model, patenting in fact is ceteris paribus *more* effective in protecting highly complex technology! After all, innovation trails of reverse engineered technology soon strand in neighboring technologies. These neighboring

technologies are very likely to infringe the patent protecting the principal technology being reverse engineered. In reality, this stranding in neighboring technologies is of course caused by the non-decomposability of technology. We see that although we cannot compare peak fitness across levels of complexity due to the complexity catastrophe, the ruggedness and peak distribution still reflect the fact that a firm is captured by the technological constraints of a design. In the presence of non-decomposability (and interface constraints and standards), we hence do not subscribe to the claim that circumvention of patents is easier for large scale, intricate technology!
We yet have to assess the intermediating role of appropriability for fixed levels of complexity. In case of no externalities, the effect of appropriability on the early mover advantage is particularly strong for high-tech sectors, which is of course caused by the diminished innovation performance augmentation. In case there are externalities, we find appropriability to generally discourage externality-opportunism. More specifically, we find appropriability to affect the collaboration propensity positively in high-tech sectors as it is more difficult to avoid infringing patents and in non-high-tech sectors because exploitation of the head start is more effective (which is caused by non-decomposability, but also due to the presence of the complexity catastrophe).

In subsection 2.3.2, we argued that the concentration is higher in high-tech sectors and that, due to the abundant technological opportunities, the level of competition is lower. Our operational model however does not have the number of agents emerge completely endogenously as we have the entry intensity depend on the concentration. The parameters for the entry intensity are exogenously set by us and fixed for all scenarios we ran. We can hence not adjust the concentration, but can however adjust the level of competition.
If we look at the combination of high complexity in combination with a low level of competition (in terms of high demand size), which we expect in the high-tech sectors, we see that the collaboration propensity is low. From a theoretic point of view, there is little pressure on dynamic efficiency and hence little urge to overcome the complexity by collaborating for complementary knowledge. If competition now rises, dynamic efficiency becomes increasingly important. Firms then have to increasingly rely on complementary knowledge through collaboration to overcome technological uncertainty and enjoy operational synergistic innovation benefits. In reality, firms moreover enjoy the incoming spillover of innovation engineering knowledge. In our model, however, there is not only no such incoming adherent spillover, but also the increase in innovation performance brought about by the collaborator is low due to the high level of complexity (and hence the strong manifestation of the complexity catastrophe).
If we look at the combination of high levels of competition and low complexity, which we expect in the low-tech sectors, we see that the collaboration propensity is high, in contrast to our expectations. Theory, after all, states that there is little collaboration in non-high-tech sectors due to the limited technological and market uncertainty. Due to the high level of standardization, the relevant intricacy is low and there is no synergistic innovation performance increase to be expected.
We see that our operational model seriously falls short here: since an agent starts out with a totally new technology (a random point in the technology landscape), it is -unlike a firm in the real world!- not able to replace the complementary components with industry standard components! The only way to overcome poor fitness is to attract an alternative agent that replaces those complementary components. So, collaboration is, here, not pursued for its *synergistic* innovation benefits or to overcome the non-decomposability, but purely for replacing complementary components!
We see that if competition increases in the non-high-tech sector, that again the collaboration propensity increases as the fitness of the -relatively independent- complementary components becomes increasingly important.

We will provide an overview of these findings in the next subsection.

7.2.6 Recapitulation of findings

Our interpretation of the simulation results has led to several interesting conclusions, factor-wise. If we now zoom out and look at the bigger picture, we note that there are some operational shortcoming due to which we do not meet our adorned TCE framework completely. As we have shown, however, if we reduce the TCE framework by imposing the theoretic equivalents of the operational shortcomings (i.e. no spillover, lack of buying and genuine internalization) and acknowledging that we cannot cross-compare propensity for the complexity factor (i.e. due to the manifestation of the complexity catastrophe), we can well explain the results we have found. We will discuss these shortcomings and the implications for our interpretation within the TCE realm of the simulation results in great detail in section 7.3.
Leaving the operational issues for a moment, let us briefly reevaluate our findings we have just presented.

Concerning our specific conclusions, we take at least three major disappointments. Firstly, as mentioned several times before, we cannot draw conclusions on the role of complexity due to the properties of the fitness measure of our technology landscape upon technological changes and changes of complexity. The fitness measure suffers the complexity catastrophe that squeezes the innovation performance benefit and oppresses the non-decomposability property. In subsection 7.3.1, we will discuss in what way the effect of complexity on 'technological performance' in our model differs from the effect that we expect in reality. Since we investigated the effect of complexity in conjunction with each of the remaining TCE factors in our two-way simulations, we see the complexity catastrophe manifesting itself in all datasets we produced (and hence also in our plots thereof).
Secondly, our operationalization of technology as a technology landscape string being generated by overly simplistic innovation causes absence of spillover in our model. Luckily, our theoretic framework does contain explanations for different levels of spillover, so we can simply reduce our framework by sitting on side of the continuum of spillover. We can then indeed derive the role of appropriability, complementarity and level of competition and compare these with our simulation results.
Thirdly, the operational R&D action options in our model lack operationalizations for market governance to purchase independent complementary components (ordinary, purchase of such technology from an ordinary supplier) and for unilateral governance to acquire expertise and internalize development of complementary components.

Even if there is no spillover (or no non-appropriable spillover, if you like), there are non-trivial interference of appropriability and externalities in determining the collaboration propensity. We discovered that if there are no externalities, 'early movers' get early access to technologies and by patenting these technology, they prevent that 'late movers' get a decent payoff. Early movers can hence build resilience, experiment longer and thereby consolidate their position. Especially if complexity is moderate to high, higher levels of appropriability are in the benefit of firms working alone. If there is a low to moderate level of externalities, appropriability positively affects the collaboration propensity. Collaboration after all aids in circumventing existing patents resting on the technology being reverse engineered. Collaboration also helps firms to exploit head starts to get to top-technologies to thereby outmaneuver competitors and build resilience. When facing high levels of externalities, but low levels of appropriability, firms tend to rely on externality-opportunism more.

Furthermore, despite the absence of spillover, there still are considerable benefits of seeking complementary knowledge. When facing ample technological opportunities during the premature phase of a sector, the ill-appraisal of projects amendments and the frequent overestimation of the fertility of joint ventures is insufficiently punished financially due to which collaboration propensity is unrealistically high. As soon as the optimists have been weeded out for being ill-efficient, the

collaboration propensity is realistic in the sense that it reflects the average innovation performance increase achievable by collaborating.
We do expect complementarity to play an even bigger role if there would be spillover, as collaboration would then affect dynamic efficiency through leaks of R&D engineering knowledge and capabilities over and above the ordinary operational (possibly synergistic) innovation performance augmentations.

We also discovered that at least a fraction of the collaboration propensity for low levels of complexity stems from what we have called 'concealed buying' or 'concealed temporary internalization of development' of complementary components.

Recall that we argued that competition amplifies the consequences of dynamic inefficiency and hence amplifies the negative effects of spillover. However, due to the lack of spillover, part of the disincentives for collaboration is nullified and the slight innovation performance increase brought about by seeking complementary knowledge appears to be sufficient for firms to seek collaboration. As said before, if there are frequent market shocks, market shares are highly volatile and if firms have only a few investment opportunities, collaboration is the best way to maximize chances of producing products that allow prolonging existence.

If we look at the intermediating effects of our operationalizations of the TCE factors under high or low complexity, we see that we do not succeed in all cases in reproducing the phenomena we expect to see in either high-tech or non-high-tech sectors.
Let us first look at the effect of complementarity. We saw that ill-appraisal of amendments initially determines the collaboration propensity, but that, with development of the technology frontier, the achievable innovation performance augmentation superposes this. However, as this augmentation is decreasing due to the complexity catastrophe, we are not sure whether this augmentation is also determining the collaboration propensity over time in reality.

Let us now look at the effect of appropriability. We saw that, in contrast to our expectations, it is relatively easy to circumvent technology of low complexity as there are many viable recombinations due to which firms generally wander off relatively far from the original design being imitated. Technologies thus developed often no longer infringe the existing patents. Often collaboration is sought to further expand the chances to circumvent those patents. If, on the other hand, technological complexity is high, we find that, in contrast to expectations, appropriation is relatively effective. Firms try to change the reverse engineered technology such that it no longer infringes the existing patent, but since the elements in complex technology are delicately interdependent (non-decomposability) this rarely succeed for firms working alone. Collaboration however does often help in circumventing the patent.

Let us now look at the effect of the level of competition. We find that firms actually do collaborate in non-high-tech sectors, but this in fact is a 'concealed buying' of complementary components. In high-tech sectors, firms actually do collaborate not only to do a 'concealed buying' or 'concealed internalization of development' of complementary components, but also to overcome incompatibilities and non-decomposability.

In table 7.1, we sum the expectations formulated in subsections 2.3.1 and 2.3.2 and our conclusions on the findings just presented.

	Complexity	Complementarity	Appropriability	Level of competition
Expectations effect of factor	Complexity induces collaboration. If complexity is high, techn. uncertainty is high. Collaboration then is statically efficient as costs of internalization and of the outsourcing contract are high. Collaboration then also is dynamically efficient as transaction costs are preferred over lock-in and sunk costs. At an operational level, high intricacy causes incompatibilities due to which the frequency of interactions increases, and hence collaboration becomes more viable.	Complementarity induces collaboration. If complementarity is low, the reduction in techn. uncertainty brought about by the collaborator is limited. If complementarity is high, intensive interaction is required to overcome incompatibilities and costs of internalization are high. Collaboration is then dynamically more efficient than internalization or externalization.	Appropriability induces collaboration. Appropriation instruments hamper opportunistic use of spillovers and lower transaction costs of externalization. If appropriability increases, hybrid and market governance forms become more attractive.	Competitions amplifies effects of other factors. If competition is fierce, dynamic inefficiency is lethal, so collaboration for complementary knowledge is instigated. On the other hand, outgoing spillover is detrimental, which discourages collaboration. The advantages of the increase in innovation performance established by collaboration must outweigh the disadvantages of outgoing non-appropriable spillover.
Expectations on intermediating effect. Expectations on sector differences		In early phases of industry development, complexity is high and segmentation and specialization make the urge for complementary knowledge (and thereby collaboration) higher. Standardization in subsequent phases reduces relevant intricacy and thereby the need for complementary knowledge (and collaboration). In even later phases, vertical integration even further reduces the need for collab. In high-tech sectors, complementarity is high and firms seek complementary knowledge through collaboration. In non-high-tech sectors, complementarity is low and firms refrain from collaborating.	App. strongly affects use non-adherent spillover. In high-tech sectors, a patent as appropriation instrument is ineffective as a patent on complex technology can easily be circumvented. In non-high-tech sectors, inherent appropriability is low as it is easy to imitate simple technology. A patent is highly effective as it easy to block imitation, but appropriation is also required. The effect of appropriation on collaboration propensity is weak (strong) if complexity is high (low). Adherent spillover occurs in collaboration under high complexity, and approp. is ineffective.	In high-tech sectors, there is high concentration and little competition. Upon increasing pressure (due to e.g. emergence of dominant design, entries) complementary knowledge is important in innovation performance. In non-high-tech sectors, there is low concentration and fierce competition. Collaboration propensity is relatively insensitive for changes in the sector and remains low.
Findings for effect of factor	Even if complexity is low, the collaboration propensity is high if the competitive pressure is high enough (e.g. if technology is mature, or concentration is low). Collaboration is then a 'concealed buying' of complementary components overcoming the lack of options for market governance. Only if complexity is high, collaborators also enjoy _synergistic_ innovation performance increases, although the magnitude is superposed by the complex. catastrophe. Comparing the results for low to high levels of intricacy, we see that the innovation performance augmentation drops (thereby also the emerging propensity) due to the regression to the mean of the fitness of optima. Fitness hence does not reflect performance and the technology landscape does not embody non-decomposability. Due to the complex. catastrophe, we can not compare propensities across different levels of complexity, nor cross-compare sectors with different techn. intensity.	Collaboration for complementary knowledge predominantly occurs if techn. opportunities start to diminish. In the onset phase, ill-appraisal of amendments is insufficiently punished due to many technological opportunities and hence yields relatively high levels of collaboration w.r.t. the actual innovation performance increases established by collaborating rather than working solo. In the mature phase, for a fixed level of complexity, the collaboration propensity increases with complementarity. The coll. propensity neatly reflects the actual innovation performance augmentation achievable as is superposed by the complexity catastrophe.	There is no substantial non-adherent spillover, and, due to lack of engineering capabilities, no adherent spillover. Still, appropr. allows early movers to build up resilience. Late entrants then fail to get market power, especially if complexity is high. Collaboration then only results in infringements and innovation performance of agents working solo is insufficient to survive. Appropriation stimulates collaboration in a sector with externalities as it helps circumventing patents and exploiting head starts. Appropriation discourages externality-opportunism and forces firms to become dynamically efficient and thereby has them resort to collaboration.	Due to absence of spillover, collaboration propensity is high if competition is fierce as it improves dynamic efficiency. If competition is not fierce, collaboration propensity is low as complementary knowledge is not required for survival.
Findings for intermediat. effect. Findings for sector diff.		In high-tech sectors, coll. would augment innovation performance synergistically due to high intricacy, but the complexity catastrophe squeezes magnitude and attractiveness. If complexity and specialization are high, ill-appraisal keeps determining coll. propens. In non-high-tech sectors, innovation performance increase is non-synergistic 'concealed buying' soon reflecting in coll. propensity.	In high-tech sectors, appropriation of design is effective as it is difficult to escape the reverse engineered design due to non-decomposability. In non-high-tech sectors, circumvention is effective due to high levels of compatibility.	In non-high-tech sectors, collaboration is 'concealed buying' of complem. components. In high-tech sectors, firms collaborate to 'buy' or 'internalize' complementary components and moreover to enjoy synergistic innovation performance augmentations (overcoming incompatibilities and non-decomposability)

Table 7.1: Conclusions on the expectations and findings on the effect of the various TCE factors in isolation or in conjunction with the factor technological complexity.

7.3 Evaluation of operational model and suggestions for improvement

In section 7.2, we confronted expectations on the effects of factors on collaboration propensity with the actual outcome and pinpointed the causes of certain discrepancies. We hereby did not find flaws in our conceptual model, but rather shortcomings in our operational model. In this section, we will elaborate on those shortcomings.

We have seen that our NK technology landscape search model (with fields of expertise) greatly determines the effect of complexity on the propensity to collaborate, as well as the effect of complementarity through its squeezing of the innovation performance augmentation. We will discuss the effects of the fitness definition and limited conception of R&D in subsection 7.3.1.
We have furthermore seen that also the component for establishing the R&D project configuration (matching of agents) does not meet the Neo-Schumpeterian premises and thereby might distort the emerging collaboration propensity. In subsection 7.3.2, we will discuss the implications thereof and stipulate the poor implementation of agent motives and interests in selecting a partner.
We also observed that the development of the sector over time as we model it does not resemble the Schumpeterian industrial dynamics. We will stipulate the shortcomings of our model to really address this industry development in subsection 7.3.3.
In subsection 7.3.4, we will elaborate on the fact that we have not (properly) operationalized market and unilateral governance and that we hence observe 'concealed buying' and 'concealed internalization of development/ expertise'. We will also stipulate that for these R&D action options to be useful, we will have to adjust our technology landscape definition.
Finally, in 7.3.5, we briefly discuss some of the shortcomings in our definition of technology with implications for (the qualities of) our operationalization of the TCE factors.

7.3.1 Shortcomings of the technology landscape search model

We already hinted in section 1.1 in the introductory chapter that preliminary simulation exercises revealed that our preselected NK technology landscape search model appeared to have flaws in representing real R&D processes. We however saw in the survey of existing (fundamental) models in section 3.1 and the survey of existing technology landscapes in 3.2 that the NK technology landscape search model is very convenient in operationalizing TCE factors. However, immediately after having operationalized the actual search heuristics in great detail in section 5.2, we issued the warning in the evaluation that our operationalization of technological complexity lacks the dimension *specificity / maturity.* Ordinarily, processes like standardization, modularization, specialization et cetera allow firms to simplify and aggregate their search and create a hierarchy of components. We furthermore noted that our operationalization also lacks the dimension *non-decomposability*, but that non-decomposability of technology rather is oppressed by the so-called complexity catastrophe. From the simulation results in section 6.3, it became clear that we indeed measure peculiar effects of (our operationalization of) complexity. Our conjecture that this is caused by the complexity catastrophe was buttressed by regression analysis of the data. So, although we argued in subsection 3.2.1 that a technology landscape primarily is a device to introduce technological uncertainty, we now know that this is not enough.
Given that we now indeed face artifacts of our technology landscape search, we, in retrospect, find it incredible that, in Neo-Schumpeterian literature, authors do not justify using a particular technology landscape in general, and the often used NK landscape in particular. We actually expect a philosophical framework that facilitates selecting or designing a technology landscape to serve the researcher best and still features the genuine properties of R&D. Now that we can tell from own experience that this common ad hoc selection of a technology landscape is a bad practice, we feel well comfortable to sum several of the main objections we thought of. In order to serve the scientific community, it is useful to pinpoint the weaknesses in the NK landscape model if it is

to be used for purposes similar to ours, such that they can either ameliorate the current model or chose a different technology landscape search model.
Our criticism focuses on two issues already mentioned before. First of all, the search heuristics to model R&D capabilities and innovation activities are unrealistic. We will elaborate and expand on issues mentioned in section 5.2.4. Second of all and by far the most important issue, fitness does not reflect performance of the whole technology, nor the compatibility of its constituting elements. Technology does not suffer grave deteriorations due to non-decomposability upon alterations, but rather regression to the mean fitness (i.e. the phenomenon called complexity catastrophe).
Largely emanating from what is discussed in this section, we will eventually call for investigation of alternative landscapes in section 7.5.

Limited conception of R&D capabilities and innovation activities

In using the NK technology landscape model, R&D is (or rather (operational) innovation activities are) generally modeled as hill-climbing heuristics, hereby just claiming that it reflects 'trial-and-error' as envisioned by Simon. We have three objections. One. We argue that the hill-climbing algorithm is not a realistic representation of the innovation process as it completely ignores the different approaches that are followed in reality. It neglects weighted search, self-restriction, depth- or breadth search heuristics and resulting subdivisions and aggregations of the landscape. Two. Due to the lack of sophistication of behavior in our heuristics, we also face some serious artifacts we had to circumvent. Three. We take our criticism one step further and not only criticize the heuristics, but actually criticize the whole conception of R&D capabilities. We will now elaborate on these three objections.

Firstly, for complex technology, innovators will indeed have to consider the side effects of technical changes and thus might indeed have to resort to evaluating effects of experimenting with one particular element on the performances of other elements. For simple, highly modular technology, however, innovators can simply optimize each individual element and each individual component in isolation, rather than merely selecting one change out of all possible alterations at a time. Improving a simple shoe does not necessarily involve considering a change in any of the elements (sole, heel, toe, material, lace, color), but can also mean adjusting only one element without having to worry about negative effects on the performance of the rest of the elements. So, while the breadth-first search reflects the nature of improvement of complex technology, improvement of modular technology is more of a depth-first search process.
In reality, firms will aggregate and subdivide their technology landscape to -if possible and desirable- confine search to natural or emergent subregions. In subsection 7.3.3, a more elaborate treatment of this process of aggregation and subdivision is given. Even when considering such a landscape region, we argue, in line with Frenken (2001), that hill-climbing insufficiently accounts for 'weighted' search that would give priority to elements that strongly affect the functions important for customers or strongly affecting overall performance. Innovation is not a process of pure, breadth-first trial-and-error, but rather experimenting with a set of elements of which it is believed that altering these elements would allow a strong increase in performance. This set of elements being involved in R&D actually changes. New elements are added and removed e.g. in the process of cost cutting, seeking niches and new segments, while other elements are discarded as particular solutions get standardized, interfaces agreed upon and options are ruled out as inferior. Firms might even expand their field of expertise in order to internalize development, keep up with competitors, enlarge the absorptive capacity, et cetera. This means that the set of elements (field of expertise) actually involved in search changes and often even due to R&D itself or by corporate strategy.
We argue that this process of aggregation, specialization/ diversification and standardization are closely related to the dimension of specificity/ maturation of technology that is so prominent in

the operational definition of technological complexity. We will elaborate on this somewhat further when we come to speak of the shortcomings in modeling industry development in subsection 7.3.3.

Secondly, apart from being a limited conception, the hill-climbing heuristic yields disturbing artifacts which we, as written in 5.2.4, had to circumvent; the increasing length of the search trails and increasing number of improvements considered for decreasing complexity. Improving modular technology would thus take longer and require more evaluation steps in total, thereby violating intuition at all fronts. During one of the validation passes, these counterintuitive effects were thought to distort the results obtained from the simulations, and in part be responsible for the failure to reproduce the central hypothesis. It was then decided to cancel out these consequences by removing costs of evaluations and having agents wrap up their R&D projects each period.

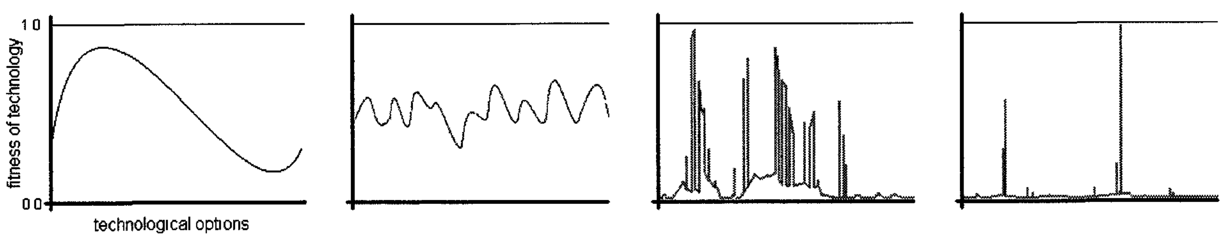
Lastly, we believe that we have to acknowledge that R&D is not just generating (possibly ingenious) technology through stupid rules, but that the R&D is a process of deliberately engineering solutions. We have to move away from reading 'unintelligent' for 'boundedly rational'. Cognitive capabilities of engineers enable them to reconstruct (part of) the map of technological interdependencies (although perhaps imperfectly) which would allow these engineers to do a sensible weighted search and departing the breadth first for a depth first search approach on the elements affected. In doing so, we really have to depart the overly simplistic heuristics and acknowledge the existence of R&D capabilities, the existence of a meta level of technological knowledge of constructing technology instances.
Over time, firms (and the individuals spanning them) accumulate believes, knowledge and corporate constraints of what starting points for technology under development should be. So, even an *invention* is not a strictly random technology, but rather is subject to believes, factual knowledge and corporate constraints.
In line with that, we criticize our own implementation of R&D as a one-shot go, a process of try-and-forget of starting with reverse engineering existing technology or by randomly selecting a technology from the whole universe of technologies, improve from there and then repeating the process. In reality, R&D is a iterative, recurrent process of improving and optimizing core technology, based on dynamically reshaped technological knowledge and innovation engineering capabilities. If R&D focuses on developing a certain product, this process often goes on as long as the pilot product is not fit enough (e.g. to enter the market) or as long as the entrepreneur believes improvements are possible. In reality, R&D often also concerns issues like deepening of the fundamental understanding of the internal workings of technology, expanding engineering knowledge, exploring new technological avenues et cetera. We clearly need to adjust our agent model to encompass such R&D.

Fitness does not reflect performance

It is stressed that the fitness does not reflect the performance of technology. We do endorse the modeling of technology as a constellation of (codes for) elements affecting the performance of one another through a web of technological interdependencies. However, rather than having fitness reflect the compatibility of the components and elements (of which the non-decomposability tells us that there are only few fully compatible combinations), we are looking at a reflection of the properties of the *arithmetic mean* of a large set of uniform random variables. Ultimately, we are looking at the complexity catastrophe in our simulation results.
Let us first discuss the properties of fitness and argue that these are unsupported for if fitness is to reflect performance. We also argue that it hence is impossible that compatibility and indeed non-decomposability is reflected in changes of the fitness value upon introducing one or a few changes in the technology. We will then try to refute our own claim by looking at the Koen Frenken mapping exercises and an additional challenge posed by Bart Verspagen. We will see that we can argue that

the fitness properties cannot reflect that of an ex ante technology landscape. We will stress that we cannot safely ignore this shortcoming in cross-comparison of emergent properties across different levels of complexity as we do here.

First of all, if we hark back on the (supposedly well-known) distribution of fitness values in NK landscapes, we argue that there is no scientific evidence that subscribes to these properties of technological performance. Especially when it comes to complex, large scale technology, it is clearly unintuitive that nearly all combinations have about equal performance, i.e. about 0.5 (50%), as freely depicted in figure 7.1b. One rather expects an extremely small fraction of combinations to be feasible (with high performance value, near 1 (100%)) while nearly all combinations are totally useless (with low performance value, near 0, completely dysfunctional), as depicted in figure 7.1d! The current technology representation as NK landscape string does not address *compatibility* of technological elements as this has a more dichotomous nature. If two technology elements affect one another (if not, they are compatible), the degree to which these two elements are compatible is expected to be often either (nearly) compatible, or (nearly) incompatible and sometimes so-so compatible rather than so-so compatible on average all of the time. Given a large number of technological elements, only a few combinations meet a certain objective, while a great many combinations do not meet this objective at all.
So, the distribution of fitness values (as depicted in figures 7.1a and 7.1b) does not reflect the distribution of performance values as we expect them to be (and as depicted in figures 7.1c and 7.1d), and the effect of the technological interdependency upon fitness does not reflect that of compatibility.



(a) Low complexity. NK (b) High complexity. NK (c) Low complexity. Real (d) High complexity. Real

Figure 7.1: The fitness of technological options (technologies) for the NK landscape and the supposedly real technology landscape, for two levels of complexity.

Second of all, we can take this one step further. In subsection 5.2.4, we already signaled that the concept of complexity as established in our technology landscape lacks the dimension of non-decomposability, i.e. that the technological elements interconnect delicately and that even little changes are very likely to bring about complete malfunctioning. This non-decomposability gets more prominent if elements are interrelated more. In the 'real' landscape, changing one or some arbitrary elements of a decently functioning technology, the performance can collapse completely. In figure 7.1d, we see indeed that a small shift to the side of an optimum causes the performance to drop to zero with high probability. It is a daunting task to get to and stay at an optimum. In the NK landscape we see quite different behavior: if we change one or some arbitrary elements, there is regression to the mean fitness! In figure 7.1b, we see that a change brings about only a small change in fitness and that before and after the change the probability is very large that the performance is close to 50%.
We then also immediately see that there must be something wrong with the rounded exercises by Frenken (2001) and Frenken and Nuvolari (2003). They show how easy it is to map the relationships of a subset of relatively large components of a particular technology onto a technological interdependency structure and subsequently show that -given fitness and interdependencies- the innovation

trajectory is self-evident. Our objection is that the Frenken mapping in fact is established *ex post* and concerns an aggregated search space and hereby thus ignores the (tremendous) complexity of the *ex ante* search space and the painstaking process in which the space is weighed, aggregated, subdivided and standardized.
If we look at the *ex ante* search space, we argue that an airplane -given the objective that it is supposed to fly- with some nuts and bolts removed is not operating just so-so. The plane is completely useless if these parts come from the engine and the plane is still completely useful if these parts are removed from the chairs on board. A model of the *ex ante* search space allows for strong performance drops for small changes in the technology specification and meets the facts that most technologies in the search space have a performance of (near) zero and that there are only a couple of technologies that meet the objective with a decent performance (indeed, there are only a few spikes in 7.1d).
How do we now falsify the postulate that this 'performance drop' is sufficiently accounted for by the ruggedness and that upon changing only a small number of elements of highly complex technology, the fitness can indeed drop into a valley and hence indicate that the technology is malfunctioning? Such a 'steep drop' does not happen in case of experimenting with technology with moderate to low complexity; the *height* of the performance drop is subject to the level of complexity.
Our objection to this is that -given that there is a simple object function- such a performance drop ~~is not only the case for highly complex technology, but also for simple technology and in general~~ for technology regardless of the number of technological interdependencies. It after all is easy to break (simple or complex) technology by replacing or removing particular elements. So, for this claim to hold, we thus have to assume there is an ex ante limitation of the search space (i.e. the set of elements and the alternatives for the various components and elements) under consideration such that tweaking of elements in a low complex technology cannot bring about such a steep drop. So, we see that, in the mapping case as well as the performance drop case, there is a need to have a limited, technologically well-defined search space for the model to really reflect the R&D process. Paradoxically, this however is part of the R&D process in form of modularization, standardization and aggregation, which we should have included in our model. So, being able to ex post construct a technology search space and its technological interdependency mapping can not justify using the NK landscape search model to represent innovation on an ex ante unknown search space.

Last of all, we are convinced that we cannot ignore this shortcoming, not even for explorative simulation research. Even if we, for the moment, ignore that we cannot be modeling a truly blind R&D process, we still face the problem that the height of the performance drop is subject to the level of complexity. Comparing the output *across different levels* of complexity is worrisome due to the complexity affecting the variance of technologies and the height of the fitness. With the current technology landscape search model, the performance drop for low complexity is small and we end up in a valley with still considerable fitness for high complexity. If we want to make this match with the -hypothetical- fact that we can replace a single element in both simple and complex technology such that it breaks (a performance of near zero), we can only do this *indirectly* by superposing a translation function from fitness to (real) performance. Given the totally different nature of the distribution, this does not appear to be a simple amplification of the variance.
Leaving the landscape for what it is and given the differences in properties for different levels of complexity, we can now only safely compare emerging propensities and other results by scaling the payoff with our market model to compensate for differences in fitness height. Note that we then rid ourselves of the complexity catastrophe and are likely to find different results for the relationship between complexity and collaboration propensity!

In 7.5, we will provide some preliminary recommendations on how to ameliorate the technology landscape search model. Those recommendations assure that the fitness measure reflects performance and compatibility, that the model exhibits the property of non-decomposability, that the landscape can well reflect an ex ante search space and that the emerging behavior from landscape search can be compared across levels of complexity.

7.3.2 Shortcomings of partner picking and matching

As discussed in section 2.2, the idea of Neo-Schumpeterian models is to have micro-level interactions induce evolutionary emerging behavioral patterns. In line with our expectations, we have seen in section 3.1 that existing models of R&D collaboration have agents that can optionally chose for collaboration over working alone and that agents have own simple heuristics to determine whether and if so with whom they collaborate. As described in section 7.1, we however have trimmed our operational model considerably so as to isolate causes of disturbing emerging behavior (which in the end appeared to be caused by the complexity catastrophe artifact) and to focus the quite weak selection forces onto as little strategy parameters as possible to support evolution thereof. We hereby replaced our sophisticated micro-level partner seeking heuristics for a simple, meso-level algorithm. This agent matching algorithm described in 5.3 then also is the most obscure part of our simulation model. Against the principles of Neo-Schumpeterian modeling premises, it is executed top-down rather than bottom-up. Furthermore, its high level of formality and its contrived form make it far from trivial to discern the economic implications. In section 6.3, we have seen that we have discovered that the so-called ill-appraisal of amendments mechanism affects the collaboration propensity. We argued that ill-appraisal is very well likely to be a real phenomenon in that highly specialized firms have a hard time in assessing the real value of a proposed adjustment as they cannot overlook the consequences of those adjustments on performance of complementary technological elements. Although we can think of and also came up with examples confirming the effects of ill-appraisal in subsection 7.2.2, we have yet only meagerly verified the effect. We still feel that we have to prove that this ill-appraisal is not an artifact of our operationalization.
We will leave further examination of the matching algorithm and the consequences for follow-up studies. In trying to grasp the role of this matching algorithm, we however came across at least two main objections, which we will discuss briefly.

Firstly, the matching algorithm does not reflect asymmetric interests. The current matching algorithm (see section 5.3) revolves around the improvement of fitness brought about to the starting technology of the principal agent by substituting components of the top-fit technology of the potential collaborator. Although this matching algorithm does have agents reject particular projects if this initial change in fitness value is too low, projects (that are not rejected) with a relatively high beneficial change in fitness are likely to be pursued. So, although both agents then have not rejected the project, the collaborator is clearly responsible for the change in fitness. We argued that there is a reciprocal complaisance, which makes lenient agents often collaborate with each other. Due to the coarse matching algorithm, we do not take into account that decisions in reality often are based on a per project basis and that firms might then have asymmetric interests and surely are led by those interest. After all, in reality, the proposed party is cautious and likely to protect its knowledge, while the proposing party is likely to accept all contributions that are beneficial enough given the outgoing non-appropriable spillover. Although we plead for a more realistic and especially a micro-level partner seeking heuristic for future models, we can already improve this model by introducing yet another yardstick such that each agent has one yardstick that is to be used when the agent in question is the proposing party and one when the agent is the proposed party.

Secondly, the matching algorithm is conceptually shallow. As mentioned in section 7.1, we were forced to simplify some components of the model. In this process, the model has lost a conceptually more meaningful 'collaborator selection' heuristic that directly incorporates complementarity (e.g. using $|E_i \cup E_j|$, $|E_i \cap E_j|$ and $|E_i \setminus E_j|$) and historic joint profit. As we have later also removed project control (e.g. specifying whether to delay investments or when to discontinue a project), it is believed that selection forces would work stronger on the collaborator selection parameters. In a next revision of this model, we would surely reintroduce these collaborator selection heuristics and see how they would now operate and affect collaboration propensity.

Note that, adjusting the algorithm to overcome these issues would not only make our agent and its partner selection more realistic and hence the emerging behavior more valid, we can isolate the effect of ill-appraisal on collaboration propensity by looking at the differences in emerging regularities.

7.3.3 Shortcomings in modeling industry development and the supply chain

Recall from section 2.2 that Neo-Schumpeterian models were established in the first place to study industry development as conjectured by Schumpeter. We hence included as a premise that the Neo-Schumpeterian model must allow studying industry development. This topic however is so immensely broad that it would require tremendously complex models to realistically (re)produce the development of industries. In practice, scholars concentrate on studying specific theories (often empirically discerned, stylized facts) and thereby devise specific, narrow Neo-Schumpeterian simulation models. This is not only more convenient, it also is necessary to overcome analytical intractability. Please realize that the results produced by a truthful model would be nearly as complex to study as the initial empirical results despite that we can actually control independent variables. Consequently, none of the Neo-Schumpeterian models adequately tackles industrial development and our model is no exception to that.

Even if we have to accept that we have to live with a narrow model, we might still fall short on implementing our own definitions with regard to the inherent dynamics of the techno-economic environment or the shaping thereof by the agents present in the system. That indeed is the case here. There are three issues. The first issue relates to the deficient implementation of the development of the techno-economic reality. The second issue closely relates to the previous issue and concerns the deficient implementation of the interrelationship of firms in an industrial sector. The third issue is a flaw introduced by coinciding of the development of the technology frontier and the evolutionary conditioning of the collaboration strategy due to which the sector development as simulated does not coincide with the sector development as intended by Schumpeter.

Firstly, the operational model does not capture the development of the economic reality. Let us for the moment say that industry development involves the co-evolution of the population, nature and strategy of firms and the technology regime. We see that we do have a changing population and (due to learning at the population level!) changes in the strategies the agents follow, but the very nature and interrelationships of firms do not change, and the technology regime is fixed. There are two problems with this co-evolution of the population (and strategies) and the technology regime that spring to mind.
The first problem is that the entry intensity does not develop endogenously. In reality, firms start to enter at large scale only when the technology starts to take shape and dominant designs are emerging. As soon as the technology is mature, certain parties tend to become dominant and start to integrate both vertically and later horizontally, which makes entry barriers high and other firms reluctant to enter. So, we see that the entry intensity is low at first, then temporarily peaks and then drops to level off at a near-zero level. In future models, we might need to make the Herfindahl inflection point shift with the survival rate of entrants.
The second problem is that the technological conditions faced by firms -and, here, that boils down to the technology landscape- do not change over time. Ordinarily, these conditions do change under influence of processes of standardization, modularization, aggregation, et cetera of the technological landscape, which go hand in hand with specialization/ diversification of firm activities and segmentation/ integration of the supply chains in an industrial sector.
Let us shortly elaborate on that. In reality, the natural boundaries of an industry gradually emerge

and firms settle around protruding opportunities, specialize and thereby bring about segmentation of the industry and standardization of technology. The intricate technological interdependencies across component boundaries and the effect thereof on performance are thereby traded for a simpler compatibility-of-components concept where the overall performance (strongly) polarizes on compatibility (which under these conditions simply boils down to whether or not the standards are followed). Such processes of aggregation through standardization occur at various levels; within firms and at sector level. In our model, as signaled before, the technology landscape does not change over time, i.e. there is no modularization or aggregation of the landscape due to standardization, no segmentation due to specialization.

If we zoom out from this subject, we see that the real search space of any technology is too large (N is extremely large) for any agent to search. Any landscape definition can easily be extended beyond sector boundaries. So, there is a part of the landscape that is normatively but more likely naturally divided and as such associated with the sector. The 'natural' boundaries of fields of knowledge, e.g. sciences and crafts, can possibly be related to the underlying technological interdependencies. To put it more firmly, particular landscape regions hardly depend on one another and one can hence then discard other regions during local optimization. We see that our random interactions of elements do not properly reflect that of a fully-fledged technology landscape. The density of interconnections should be heterogeneous. There should be clusters of strongly interconnected elements. We believe that firms settle on such clustered subregions as their product then has considerable value for customers that would otherwise also have to develop solutions in that technologically complex subregion.

We conclude that our operational model falls short in having agents adjust their field of expertise to cover or add regions of highly clustered elements. We also see that agents cannot issue standards, thereby aggregate the technology landscape search and shaping the technology regime faced by agents. So, although the intricacy of the technology remains the same, the regime becomes aggregated and hence the difficulty of R&D and technological complexity drastically diminishes. We see that if we would have committed ourselves to implementing all dimensions of the definitions of technology and technological complexity as formulated in section 1.3, we would have been forced to implement activities such as standardization, modularization, aggregation, specialization et cetera. In section 7.5, we will recommend a simple design that takes a first step toward an implementation thereof.

Secondly, the operational model does not encapsulate the interrelationship of firms in an industrial sector. In our discussion of the previous point, we already noted that the operational model lacks specialization/ integration. Apart from the fact that we thereby miss the effect thereof on the technological regime as relevant for the firms active in the industry and thereby on the technological complexity and R&D strategies followed, we also miss the effect on the interrelationship between firms active in an industry. In our model, we instantiate a set of agents with certain technological capabilities (i.e. their field of expertise) and have them produce technology that is sold on the same market by all agents. Agents hence are direct competitor as they serve the same customers. We hereby completely neglect the fact that an industry usually is organized in a supply chain (that got its shape over time through actions of specialization/ integration related to the development of the technology regime as relevant for R&D) in which firms specialize in manufacturing certain components, buying subcomponents and material, selling to some other assembling firm or to the end-consumer. In our model, we do not have such buying/selling relationships between agents. The agents only compete on the market for the favor of the (aggregated) end-consumer, on the one hand, and collaborate *horizontally* in developing a product, on the other. In reality, if a firm starts developing a new product, it selects a set of standards it is going to follow, then seeks suppliers of that complementary technology. Within the degrees of freedom thus remaining, the agent will start to look for innovations to its own current technology. We already concluded that part of the collaboration propensity we measured also stems from the fact that agents 'buy' complementary technology to overcome the limited fitness of the complementary components.

Thirdly, the development of the sector while running the simulation does not only fail to capture the development of the economic reality, we are also looking at onset disturbances that unfortunately coincide in time with what ordinarily would be the deployment of the sector. As specified in chapter 5, we start out with a particular strategy population that is about the same in all simulation runs. In the first stage of the simulation, both the technology frontier develops as well as the strategy population is subject to change. The results are still distorted by the presence of insane strategies. In the meanwhile, the technology frontier progresses and levels off, causing the strategy population to be conditioned to survive under these conditions. In reality, there is, first of all, not only population level learning, but firms adjust their (collaboration) strategy during their life-time, and, second of all, also the initial firms have a predetermined collaboration strategy, such that the strategy population is not a random mix. So, we have to be careful with extrapolation of the collaboration strategy in the onset phase in the simulation results to the collaboration strategy in reality. It would perhaps have been more interesting to endow agents with a heuristic, variable collaboration strategy rather than a static yardstick strategy and to run a Yildizoglu style genetic program (either to train the strategy in simulation runs prior to executing the simulation run we register, or during the simulation run itself).

In sum, not only does our model lack the effect of agent actions on the technology regime as relevant to the agents themselves in R&D, it also lacks agent action options to shape the interrelationship between agents (as partially based on the developments of the technology regime) to form a supply chain or genuinely portrait the development of the entry/exit intensity and market concentration. We further see that part of the development of the industry that we do actually model coincides with the evolutionary selection of the collaboration strategy and thereby pollute the propensity measurements. In subsection 7.3.4, we will show that our omission of several action options also causes incomplete operationalization of our adorned TCE model.

7.3.4 Shortcomings in R&D options in operationalizing the TCE framework

Initially, we started out with experimenting and exploring different simulation models (also see 7.1) based on hunches rather than proper grounding in an operational model or conceptual framework. We had to prune the operational model and simulation model several times for us to reduce the variance in the results and to get the model to produce interesting results.
After this experimentation, we started to form our presumptive and stylized rationales for collaboration into a conceptual model. After deliberation, we decided to based the conceptual model on the traditional TCE model (rather than loose Strategic Management theories). We had certain presumptions on what kind of activities were involved in this R&D process. We had to model, so we argued, the genuine innovation process in which researchers need to constantly reshape their image of the technology they are developing based on constantly gained insights. This would hence concern frequent, reoccurring transactions requiring project specific investments. From these presumptions, we formulated two assumptions in subsection 2.3.1 that allowed us to reduce the traditional TCE framework to a specific framework concerning the transaction of technological knowledge while conducting R&D. First of all, we assumed moderate to high asset specificity. Second of all, we assumed moderate to high frequency of transactions. These two assumptions allowed us to reduce the R&D action options of a firm to either seek bilateral or unilateral governance (See the table in figure 2.1). We therefore reduced the action options (R&D strategies) available to working alone in improving an invention (unilateral governance) and collaborating in improving an invention (bilateral governance). Note that we, by that time, were, by and large, already working with the current operational model and hence were tempted to simply associate working solo with unilateral governance and collaborating with bilateral governance. It must be said that, in an earlier stage, at least

the most simple alternative activities required for industry development (also see subsection 7.3.3) like expanding, reducing and shifting the field of expertise have been discussed. At that point in time, we decided to leave the operational model for what it is.

However, during analysis of the results, we concluded that at least a fraction of the collaboration propensity stems from a 'concealed buying' of complementary components or, alternatively, a temporarily 'concealed internalizing' of expertise. We hence conclude that the action options available to the agents in our operational model are too limited and that we thereby render this peculiarity of 'concealed buying/ internalizing' in emerging behavior. In subsection 7.3.3, we already concluded that our operational model falls short in having agents adjust their field of expertise. Here, we however also conclude that buying components (abiding by certain standards) complementary to the field of expertise should also be added to the action options.
So, we now stress that our operational model has one of the following two shortcomings in action options, or even both. The first shortcoming stems from the interpretation that this 'artificial' collaboration propensity for low complexity is 'concealed buying'. In that case, we must conclude that we overlooked the fact that much of the R&D trail is not pure innovation, but also concerns simple integration and supplementing the invention with existing (standard) complementary components. The second shortcoming stems from the interpretation that this 'artificial' collaboration propensity is 'temporary concealed internalization of expertise' (or, alternatively, of development of certain elements, of course). In that case, we conclude that we have not properly implemented 'unilateral governance' and that we should, as stressed in subsection 7.3.3, endow agents with the ability to relay and/or expand their expertise, also semi-permanently. In that case, we model that a firm sometimes internalizes the development of the complementary component.
Note that, theoretically, internalization is likely to occur if complexity is high (and spillover non-appropriable and sensitive), while buying and outsourcing are likely to occur if complexity is low. Extending this line of thought, we argue that we have discerned 'buying/ outsourcing', not 'temporary internalization'. However, in retrospect, it is likely that not just part of the collaboration propensity we measure for low to moderate levels of complexity is 'concealed buying', but that part of the collaboration propensity we measure for medium to high levels of complexity actually is 'concealed internalization'.

We hence stress that the R&D strategy options that can be followed by agents should be expanded to a Markov-chain of unilateral innovation, multilateral innovation, outsourcing innovation and buying components. Ideally, we should also include action options like abiding or formulating standards, modularizing own technology to aggregate the search space, et cetera, i.e. those actions that aid in operationalizing the development of an industry and supply chain.
If we extend our line of reasoning (and in fact also that of Teece (1986)), R&D conducted for independent complementary components concerns investments in non-specific assets and would hence then be purchased from a supplier or their development outsourced (hereby providing interface constraints), while intricately related complementary components can be developed in collaboration or outsourced. The Markov-chain state transition mechanism would allow iterations of such actions.

If we however do so, we face another issue with our technology landscape. Ordinarily, the technological interdependencies are heterogeneously distributed, while in our NK landscape the interdependencies are homogeneously distributed. The technology landscape generally has clusters of strongly interrelated elements that have little or no dependencies with other clusters. Mind you that such clusters can be natural or artificially created by standardization and modularization (also see subsection 7.3.3). In conducting R&D, firms face a technology landscape made up of components, some of which are intricately related to their own core technology and some of which are relatively independent. It is easy to see that they can simply purchase non-intricately related (i.e. relatively *independent*) complementary technological components on the market, through common supplier-channels (if available) or by outsourcing; there are no incompatibilities to rise and this

is not only a relatively incidental, at least not ongoing reoccurring transaction, but also concerns generic assets requiring nonspecific investments.
In case of intricately related complementary components, firms cannot simply purchase these components as use thereof is bound to yield many incompatibilities deteriorating the technology performance of the technology yet to develop. The principal firm is then likely to pursue collaboration with firms that produce intricately related (i.e. strongly *interdependent*) complementary components or, under other circumstance, to internalize the development of these components. Either of these options would not only allow the principal firm to enjoy synergistic innovation performance augmentation but also simply to integrate the technological components thus supplied.
So, when we decide to add 'buy/ outsource' and 'internalize expertise' to the R&D action options of our agents, we are forced to introduce clusters in our technology landscape and endow our agents with some sensor for intricacy of elements inspected.

7.3.5 Further shortcomings of our operational definition of technology and implications

In this subsection, we will stipulate some of the shortcomings that are not directly related to the Neo-Schumpeterian premises, nor related to any of the major model components (NK landscape search, matching, market et cetera), but rather concern shortcomings of our operationalizations of TCE factors with respect to their theory as a direct consequence of our limited conception of technology. Our conception has three shortcomings. First of all, we saw in subsection 7.3.1 that we did not implement non-decomposability by opting for the NK landscape. Second of all, we saw in subsection 7.3.3 that we did not implement the dimension maturity/ specificity of technological knowledge since we omitted implementing specialization, standardization, aggregation and the like. Third of all, we saw in subsection 7.3.1 that we oversimplified the R&D capabilities as we reduced R&D to generating a technology instance by following a simple hill-climbing heuristic. We stressed that not only our heuristics are too simple in that there are no weighing or search tactics, we also completely ignore the fact that technology is also deliberately engineered, and that there hence is a technological knowledge base. This last issue results in two disconcerting shortcomings: firstly, we are not able to model spillover and thereby frustrate the effect of appropriability in our model and, secondly, we are not able to model complementarity completely as there is no such thing as adherent learning or R&D engineering knowledge. We will now discuss both these shortcomings briefly.

Appropriability: no spillover

There are several issues that relate directly purely to our conception of technology as an 'instance'. We already argued in subsection 5.4.3 that the effect of spillover is limited, which is attributed to the extremely low probability of encountering the same combination (out of 2^N possible combination). In section 6.4, we saw that our simulation results confirmed this. So, with this particular technology landscape, we can insufficiently model (direct incoming and outgoing) non-adherent spillover, since transfer of a few instances is really insubstantial. In reality, spillover not only concerns a 'recipe' of the technology, but often rather concerns knowledge of the underlying technological interdependency map, accumulated knowledge on why particular technological configurations are to be chosen. So, we have to acknowledge that there also is something like R&D capability and engineering technological knowledge. As we already observed, our model does not contain technological or innovation engineering capabilities, so such adherent spillover is absent.

Complementarity: learning

The understanding of the relationship of technological complementarity, on the one hand, and learning and technological knowledge, on the other hand, is limited. This hampers devising a proper operationalization encompassing both. In this essay, we have succeeded in operationally defining technological complementarity, but due to the narrow conception of technology -in that we conceive technology purely as instance- we fail to bridge the gap to also incorporate capabilities and the knowledge base to engineer such instances.
In our exposition of the conceptual model, we argued that collaborating agents should not be too close to each other, but also not too far from each other in technological capability space to optimize the novelty value of the relationship and learning capabilities. As we do not model R&D capabilities, there is no learning in this sense!

So, we -again- opt for an innovation engineering knowledge base from which information can be transferred from one agent to another in the form of (adherent) spillover. This knowledge should then increase the innovation performance and dynamic efficiency in generating novel products. The learning of one agent from another then resides in the adequate absorption of such leaked innovation engineering knowledge. Such adherent spillover then of course also is an incentive to collaborate and the partner selection then not only relates to additional competences or recipes or instances of technological components of but also to the possible influx of complementary innovation engineering knowledge.

7.4 Reformulated understanding of R&D collaboration propensity under technological complexity

From section 7.2 we know which flaws in the operational model cause the discrepancies between expected effects and obtained simulation results and from section 7.3 we have a thorough understanding of the consequences of the operational shortcomings. In this section, we will use that gained understanding to implicitly translate operational shortcomings into restrictions to our factors in our adorned TCE model and use that to reformulate the relationship of technological complexity with the R&D collaboration propensity.

Let us first shortly recapitulate our adorned TCE model as we have formulated it initially. To go short, R&D collaboration propensity depends on the magnitude of the innovation performance augmentation (i.e. the increase in performance that is established by collaborating rather than working solo) is estimated to bring about. High technological complexity limits own R&D performance and makes complementary knowledge and capabilities valuable in overcoming those limitations. This not only concerns static, but also dynamic efficiency gains. If competition becomes more fierce, such incoming efficiency gains become more important in own survival, but the non-appropriable outgoing spillover also becomes more detrimental. The collaboration propensity thus reflects the net benefit of incoming innovation performance augmentation and outgoing non-appropriable spillover.

In discerning the fundamental operational mechanisms shaping our simulation findings, we have found several interesting causes of the collaboration propensity, which can indeed be deduced to closely relate to these two terms. We will hark back to our description in section 7.2 of the effects of the operationalizations of TCE factors on collaboration propensity (which we relate to the fundamental operational mechanisms), and turn our exposition of these effects inside-out to describe the reasons for collaboration from configurations of these factors. In our description, we will distinguish immediate, static and dynamic efficiency arguments.
Finally, we will reevaluate the relationship of complexity and R&D collaboration propensity with the gained understanding of the operational (dis)advantages of collaboration and the role of TCE factors therein.

7.4.1 Effects of R&D collaboration and the reformulated role of TCE factors

As far as the immediate, *static* efficiency goes, the achievable innovation performance augmentation dominates the explanation.

The overall collaboration propensity immediately drops upon a decrease in actual achievable performance augmentation, which might be caused by, e.g., -in case of reverse engineering- progression and tightening of the technology frontier or by external/ artificial circumstances like the complexity catastrophe squeezing the achievable performance augmentation.

Unlike our expectations, collaboration propensity is not higher for a higher level of technological complexity, since the positive (and even synergistic) effects of collaboratively conducting R&D (i.e. signaling incompatibilities, integration of complementary components, preemptive redirecting innovation trajectory) are virtually nullified by the low achievable innovation performance augmentation caused by the complexity catastrophe. On the other hand, we do measure considerable levels of collaboration for technology of low to moderate complexity. In contrast to the reason for collaborating in case of complex technology, there is no synergy and there furthermore is no substantial spillover, let alone adherent spillover of complementary technological knowledge. Part of this propensity is caused by the 'concealed buying'/ 'concealed internalization' by absence of such action options in our operational model. We expect the collaboration propensity to be lower in reality, since firms can simply purchase that supplementing technology from a supplier or outsource its development. Furthermore, the performance augmentation (that might then not be synergistic in nature) is considerable, so collaborators are certainly not punished for poor innovation performance.

When firms face fierce competition (and would be forced into demise in no-time if they do not come up with top-fit technology) and thereby suffer no non-appropriable spillover, they strongly rely on collaboration to enjoy the complementary knowledge and thereby having a higher chance of finding a top-fit technology. If innovation performance is less of a prerequisite (e.g. due to a lenient, large market), we observe that firms no longer resort to collaboration.

It should be clear that structural static outstanding innovation performance often translates in higher survival rates and hence is an indication of dynamic efficiency. Hence, for instance, the direct reflection of performance augmentation in the simulation results for the effect of complementarity on collaboration propensity. Once evolutionary forces have wiped out dynamically inefficient firms that would ordinarily distort the propensity picture with inferior R&D collaboration strategies, the surviving firms have an eagerness to collaborate that nearly perfectly reflects the achievable innovation performance augmentation, even if they ordinarily suffer from ill-appraisal of project amendment! This is a neat example of how evolution reverses the causality. Please realize that the actual magnitude of the achievable innovation performance augmentation also immediately affects the accuracy of the selection forces, so, if the complexity catastrophe squeezes the augmentation, the results are more polluted.

As far as the less obvious *dynamic* efficiency goes, we found that the collaboration propensity often depends on whether or not collaboration enables the principal firm to build resilience for market shocks. Ordinarily, spillover would impair dynamic efficiency, especially if complexity is high as we then expect considerable levels of spillover of adherent engineering knowledge. Here, however, spillover is absent both in adherent as well as non-adherent form.

Dynamic efficiency now however is still affected by externalities. Let us look at the two dimensional space spanned by the level of externalities and the level of appropriability (excluding the case that both are low). If there are externalities but little to no appropriability, firms tend to be soloist (little collaborative) as they can rely on the influx of externally generated technological knowledge. If appropriability however increases, firms tend to swap their soloist attitude and engage in collaboration as that allows them to build more resilience. Not only does collaboration then help to circumvent the longer protected reverse engineered technology, but also because the firms generate fitter technology together, which (since this technology is patented for a longer period)

generates more total payoff and it hence is more rewarding to collaborate in the end. In these cases, the eagerness to collaborate of firms is such that they build as much capital stock as possible such that they have some slack in dynamic performance during which they can consolidate their position.
If externalities (and spillover) now are absent and the level of appropriability is moderate to high, we see that firms again are soloists, largely caused by the fact that early mover soloist receive more payoff per capita, which allows them to building resilience and consolidate their position. This is particularly true for high levels of complexity due to the steep drop in achievable innovation performance augmentation and thereby the more obvious advantage of working solo.
We also expect the collaboration propensity to be more polarized in reality than in our results, especially if complexity is high. In that case, firms would ordinarily also enjoy/ suffer *adherent* spillover of innovation engineering knowledge. If the level of competition is high enough to severely punish dynamic inefficiencies, while the appropriability is relatively high compared to the level of competition, there will be more collaboration than our model predicts. In other cases, we expect less collaboration. In reality, spillover determines for a considerable part the reservation to collaborate.

7.4.2 Reformulation of the refined and operationally buttressed TCE framework

We now have a thorough understanding of the consequences (in terms of the static and dynamic efficiency) of collaboration and in what way complexity (as well as our other TCE factors) play(s) a role. The model designing exercise and our critical appraisal of the flaws gained us a profound understanding of the (dis)advantages of collaboration and the (possible) role of the operationalized TCE factors therein. Based on this profound understanding, we reformulate rationales for collaborating in R&D through appreciative theorizing.

We argue that collaboration in case of complex technology occurs often to reap the synergy in overcoming incompatibilities, integration of complementary components and preemptive redirecting of innovation trajectories, but the relatively large asymmetric outgoing *adherent* spillover of technological and innovation engineering knowledge is difficult to appropriate and thereby forms a serious drawback. On the other hand, the market is relatively concentrated and due to the relatively high level of specialization, opportunistic collaboration is relatively rare. Thereby, the *non-adherent* spillover of technology 'recipes' can be effectively appropriated due to the non-decomposability caused by the intricate interrelationships.
Since interdependencies are not homogeneously distributed, there are natural subregions in the landscape. Relatively independent components are acquired through market governance. If more intricately related components are purchased, we expect at least some level of collaboration to accompany integration. We acknowledge that part of the collaboration propensity might stem from over-valuation of what collaborating can do in innovation performance.

We argue that collaboration in case of simple technology rarely occurs as buying or outsourcing of the development of complementary components yields little efficiency losses due to incompatibilities, and there are no additional synergies to be expected upon internalization or collaboration. We argue that returns from innovation are hard to appropriate, since circumvention is easy due to the high levels of compatibility and hence with little impact on technological performance. The spillover generally is non-adherent, and furthermore has a high externality character due to the commonly available knowledge making outgoing knowledge easy to imitate and absorb for competitors. The combination of fierce competition and highly absorbable non-adherent spillover on highly compatible complementary technology that allows for near-immediate entry makes opportunistic collaboration likely.

Although our operational model produces results that contradict our main hypothesis, the thus established integrated view on the collaboration propensity under technological complexity in fact supports the main hypothesis.

7.5 Suggestions for further research

Now that the research has been wrapped up, we can look back and formulate suggestions for further research. We believe we have realized some considerable achievements. First, the refinement, synthesis and adornment of the TCE framework. We see that our initial formulation in subsection 2.3 is robust and, as we see in section 7.4, can be buttressed operationally. Second, the establishment of the operational model allowing operationalization of factors in this adorned TCE model in the Neo-Schumpeterian framework (and thereby testing the relationships in that model). Third, the discerned fundamental mechanisms at play in determining the collaboration propensity and their development (and showing the workings thereof formally). Fourthly, our critical appraisal of the adorned TCE model and the operational model.

We believe that the adorned TCE framework in fact is promising, but, as we have seen, the operationalization of the factors in the adorned TCE has several flaws and, despite that the framework has been shown to be robust, we feel that our adorned TCE framework should be put to the test more. We will discuss this in more detail in subsection 7.5.1.

The fundamental mechanisms we have found driving collaboration propensity are intriguing and we are for sure interested to what extend these mechanisms are at play in reality as well. In subsection 7.5.2, we will hint on some of the issues that one might want to look at.

In section 7.3, we have placed serious remarks by the landscape component of our operational model as we discovered that it thwarts our operationalizations of definitions and concepts in our adorned TCE framework. The suggestions for further research then also concern investigating and deepening our understanding of the design and properties that technology landscape search models must have to properly reflect a 'real' technology landscape faced by firms. We will go into that in subsection 7.5.4.

We have also seen that there is a lack of certain actions options (corresponding to (technological) capabilities of firms) and 'strategic' R&D options for the agents. This not only distorted the collaboration propensity we measured at an operational level, but also entailed absence of industry development and development of the technology regime agents face. We will provide pointers for specific follow-up research in subsection 7.5.5. More specifically, due to our narrow conception of R&D engineering capabilities, adherent spillover is absent in our model. Due to this, we were hence in fact looking at only a part of the adorned TCE framework (without spillover and/or with all spillover perfectly appropriable, that is). We describe this in more detail in subsection 7.5.6.

Related to the aforementioned issues, we stress that our implementation of finding a collaborating party is not realistic enough. If we add more action options, we argue that agents should be equipped with capabilities to select a preferred agent to outsource R&D to, buy technology from, working together with et cetera. We describe that in more detail in subsection 7.5.7.

7.5.1 Have the adorned TCE model contested

One of the flagships of this essay is the adorned TCE model as established in 2.3.1. We, first of all, refined the existing TCE model and disaggregated it which allowed us to tackle critique and pending requirements. We showed that it is very well possible to adorn this refined TCE framework with primary, specific Strategic Management theories without having to garble interpretations. We also saw that we even are able to interconnect context free, operational definitions of technology, complexity, spillover, et cetera, with the SM theories and -in one go- cover the forces at work in the more traditional terminology. This, by the way, convinced us that it is not an objection to depart the slightly unnatural, contrived terminology of the tradition TCE and rather allow ourselves to use the more common strategic management terminology.

In section 7.2 we have seen that this study has not been a real test for our adorned TCE framework. We have seen that we can well translate our findings in the adorned TCE/ SM terminology and easily interpret and explain the phenomena observed, but we have also seen that our operational model has several flaws that, of course, limit the internal validation. In section 7.4, we have reformulated and refined the TCE with gained understanding. We have seen the the old adorned TCE holds more or less entirety. As this however still concerns appreciative theorizing, we feel that we still need to properly assess the predictive qualities of an operationalization of the adorned TCE framework in the controlled, experimental setting that this simulation exercise has formed.
We believe this adorned TCE model is well worth some additional attention, either by empirical analysis, simulation with alternative operational modules for appreciative theorizing, further synthesizing with alternative theories or just plain intellectual contesting.

7.5.2 Verify suggested motives for collaboration

In our effort to grasp the results, both during data-analysis and the interpretation of conclusions in the realm of the adorned TCE model, we have put forward several mechanisms and drew preliminary conclusions on the motives and beliefs of firms to engage in collaboration. Here, we briefly sum the most important ones and call for a follow-up study to empirically confirm the existence thereof.

One of the most important motives for collaboration is the signaling of incompatibilities across competence boundaries. This motive is primarily at stake in non-mature regimes in which interfaces are ill-defined. This motive is also at stake when the concentration in the industry is dropping and competition drives firms to look for an alliances to target synergistic innovation in overcoming currently standing technical standards (and thereby win efficiency). Empirical studies can investigate the extent to which there indeed is reintegration of technological components in mature industries, or the extent to which firms indeed engage in alliances with early-warning systems in the form of highly integrated R&D with frequent reviews.
In the light of considerable externalities, we proposed two other motives for collaboration that appeared to be indistinguishable in the data: patent circumvention and exploitation of head starts. Empirical studies could investigate the extent to which there indeed is imitation of technology and vigorous pursuing of complementary knowledge in adjacent disciplines in overcoming infringement of crucial patents.

There also are certain beliefs that can make firms wanting to collaborate. We already discerned the ill-appraisal mechanism at work, which in fact reflects that hyper-specialistic firms overvalue collaboration. As we already said, we do not quite know whether this is or is not an artifact of our operational model. Part of the ill-appraisal in the onset phase of the simulation (which is not the sectoral development phase in the real world!) is also caused by the fact that part of the firms still are overly positive as far as the contribution of collaborators goes. A closely related question hence is whether the collaboration propensity really reflects the achievable innovation performance improvement. To answer this last question, we of course have to isolate technological benefits from other benefits like market access and financial risk sharing. One might conduct a longitudinal study in various sectors to check whether there is a structural over-optimism or rather realism about collaborating if one compares the ex ante collaboration propensity with the ex post benefits accrued to collaboration.

7.5.3 Deepen philosophical understanding of requirements of technology landscape

At the outset of this research we selected the popular and promising NK landscape search model to represent R&D. In section 3.2.4, we showed that the NK landscape indeed allowed operational definition of nearly all our TCE factor immediately and furthermore has an operational definition of technology that -to some extent- fits the definition of technology we provided in the demarcation section 1.3. However, already in the introductory section 1.1 of this essay, we hinted that exploratory simulations and experiments with previous operational models made us suspect that certain properties of the landscape search model introduced peculiar model behavior. We pointed out that we would also take the opportunity to evaluate certain properties the NK landscape search model. Given our research design, we would either end up with supporting our main hypothesis and implicitly approve or criticize the landscape search model and thereby not being able to support our main hypothesis.

As treated elaborately, the simulation results presented in section 6.3 contradict our main hypothesis and we discerned (and buttressed with regression analysis) the fundamental mechanisms that clearly indicated we in fact are looking at artifacts of our landscape search model. After seeing the landscape flunk, we felt comfortable to provide some criticism on the technology landscape search model in subsection 7.3.1.

We recommend starting fundamental research aiming at a philosophical understanding of the properties a technology landscape; the framework defined in section 3.2.1 apparently is not all-encompassing. It was argued that the single most important feature of a technology landscape is that it introduces uncertainty in search outcome. We however have seen that it is crucial that particularly the operationalization of innovation derived from the landscape should, for instance, meet the stylized fact that even small changes in technology are likely to bring about malfunctioning or complete dysfunctioning of technology through the intricate web of technological interdependencies. A technology landscape should to that end have a technological performance measure that expresses compatibility between elements and components and reflects non-decomposability. We should perhaps integrate the operational definitions presented in section 1.3 or make these even the premises of any landscape! The next subsection will elaborate on improving the technology landscape by incorporating this definition.

7.5.4 Adjust technology landscape: meet properties of technological complexity

As an immediate consequence of the issues discussed in subsection 7.3.1, we take a bold stance and argue that the current 'arithmetic mean' fitness in our landscape is not correct and that the calculation of 'fitness' (or rather performance) of a technology should reflect the actual nature of the relationships of elements.

Since we first need a proper philosophical understanding of the requirements of a technology landscape (as argued in subsection 7.5.3), we just provide an example of an alternative technology landscape rather than providing operational definitions for each dimension of technological complexity (see section 1.3).

We take the liberty to propose just one example of an alternative technology landscape model that expresses performance predominantly in terms of compatibility of elements by means of multiplication of 'combination feasibility' variables $F_i(T[i])$. Each element has a relationship with -on average- K other elements that determine the extent to which that element is 'working'. We propose that the feasibility F_i of an element i depends on its own functioning $F_i(T[i])$ and the product of the compatibility F_{ji} of all elements j that affect the functioning that element i. Hereby $F_{ji} \sim Beta[a, b]$, where $a = b = 1/n$ with $n \gg 0$. Note that the lion-share of the F_{ji} values then either is very close to 1 or very close to 0. Even a single incompatibility (F_{ji}) would immediately make the whole technology malfunctioning (i.e. with performance ~ 0).

We do not claim this multiplicative model is all-encompassing, but it must be seen as an indication that there are more interesting technology *instance* models (as opposed to technology *capability* models). In the grand scheme of things, this proposal actually is a call for acknowledging that there is a yet undiscovered algebra to define the underlying structure of technology where e.g. some components simply 'add value', while other components nearly completely 'determine the overall feasibility' and yet others affect overall performance according to an 'arithmetic mean' operation. It is stressed that we have to acknowledge and model the full complexity of the technological structure, rather than relying on an abstract model to just introduce uncertainty and that otherwise has properties (e.g. no non-decomposability, awkward performance behavior for changes in intricacy) that are ill-accounted for. With a proper technology landscape, the researcher should be able to study the effect on emerging properties and agent propensities across variations in those algebraic expressions of technology structures without actually looking at artifacts of the technology landscape as we do now.

So, we call for a follow-up study to contrive instance landscapes adjacent to the NK and multiplicative Beta landscape and to investigate the properties of the derived conception of innovation. If the technology conception would allow more of a hierarchy of technological elements and components, we might even progress toward an algebraic system to express technological interdependencies.

7.5.5 Deepen conception of technological capabilities

Although we stressed the requirement for a simple model in chapter 4, we ran into serious consequences of our oversimplification of the agent model. With respect to the technological capabilities of an agent, we suggest two alterations: add self-redirection to the technological capabilities (i.e. the field of expertise shifts over the landscape) and add an (implicit) secondary market at which components for complementary capabilities can be bought (or even licensed by passing on a predefined fraction of the payoff). In subsection 7.3.4, we even suggested having agents navigate through a Markov-chain of actions allowing agents for instance to buy and/ or outsource development of relatively independent complementary components, (semi-permanently) internalize development of certain highly related technological elements and collaborating on large, related components. At a strategic level, agents might then be engaged in processes like diversification or concentration on core competence, specialization or integration et cetera, which might, at industry level, bring about or clear out segmentation.

In subsection 7.3.3, we elaborated on the shortcomings of our operational model in modeling industry development under the influence of processes of specialization, standardization, aggregation, et cetera. Such activities would divide the technology landscape as 'relevant' to the agents into subregions. Our model hence also does not incorporate the fact that collaboration often is a mean to bridge the gaps between knowledge bases. R&D often is intersectoral and interdisciplinary and targets cross-fertilization knowledge from different disciplines. Here, agents -although their fields of expertise are different- belong to the same sector as they compete directly by serving the same market.

For future research, we propose the following improvements. Firstly, introduce 'natural' clusters of interconnected technology elements and allow the endogenous introduction of standards that 'fix' the specification of elements (that possibly/ are likely to connect to other of such natural clusters) to thereby form an interface. Secondly, allow agents to alter their expertise to seek interesting patches on the landscape and draw the technological component for the complementing expertise from other agents (creating a sort of supply chains) and hereby creating secondary markets in which agents are not selling directly to the primary market of end consumers. The expectation is that the patches will generally coincide with the natural clusters.
Implementing these two improvements would allow for specialization around natural subregions, and hence segmentation and formation of supply chains, and -due to specialization- increasing standardization and hence progressing of segmentation and in the end endogenous modularization of technology into an hierarchy of components (at least for downstream, 'assembling' agents). We

expect co-evolution of the nature and structure of firms and the perceived complexity of the technology landscape.
By implementing these improvements, we also allow agents that now start with completely random technology to replace (complementary) components with component specification that can be purchased at secondary markets from 'supplying' agents with different fields of expertise. Collaboration then no longer is a concealed purchase of complementary component technology, but really an attempt to enjoy synergistic innovation performance increases.

In discussing the different governance forms once an agent has decided to engage in R&D, we almost forget that firms need not be involved in R&D all the time. Recall from section 7.1 that we have removed certain agent functionality in early model design phases to isolate and ascertain the causes of our contradictory findings. In doing that, we removed a strategy that decided to conduct R&D or not, i.e. make innovation *optional*. It is suggested here to reintroduce that as an action option. Note that this would enable us to test Katz' proposition that competition is a disincentive for collaboration.

In short, by expanding the low-level technological capabilities of agents, we would, first of all, overcome the shortcomings in action options mentioned in subsection 7.3.4 and thereby rid ourselves of the 'concealed buying' and 'concealed internalization', but also compulsory rather than optional R&D. We then, indeed, also operationalize more of the governance types mentioned in the TCE framework (see subsection 2.3.1). Second of all, we would also do a quantum leap toward overcoming the limited industry model as discussed in subsection 7.3.3.

7.5.6 Replace simplistic innovation heuristics by non-unintelligent engineering capabilities

Apart from the lack of self-redirection, we discovered yet another obstacle that is to be overcome if we are targeting a universally valid technology landscape model. In instance technology landscapes, the effect of leaking of an instance to represent spillover is relatively insignificant. As described in section 7.3.1, we firmly believe that the commonly adopted narrow conception of R&D activities is a harmful oversimplification and that engineers sometimes conduct depth-first, weighed search guided by engineering knowledge. We also believe that engineers are engaged in processes of aggregation and disaggregation of the search space, expansion and narrowing of the scope of research, et cetera. We argue that R&D personnel is endowed with innovation engineering knowledge and capability sets that enables them to actual purposefully engineer innovations in a non-unintelligent manner that is far from purely heuristic.
We recommend investigating operational R&D practices to add realism to our technology conception and landscape search heuristics models. If our models of technology and R&D are more realistic, spillover then not only takes the form of leaking instances, but also leaking knowledge on weights, operational search heuristics, engineering knowledge, levels of aggregation of research, interesting regions for divestiture and scope expansion, et cetera.
Recall that we would then also have to refine our conception of appropriability rather than protecting a single technological component. If agents have innovation engineering knowledge and capabilities, also the application of particular knowledge might be appropriable. This is an interesting research avenue.

7.5.7 Adjust agent selection strategies

In subsection 7.5.4, we did suggestions to improve the performance distribution of the landscape such that it reflects compatibility between elements (and components) and ultimately the non-decomposability of technology. That would obviously alter the properties of search and search outcome, and eventually the collaboration propensity emerging. Closely related to this, we did suggestions to adjust the actions available to agents, endowing the agent with options to attune the governance form chosen to the sections of the landscape it intends to improve. We argued that especially for intricately related components or subregions of the landscape, the agents would be inclined to collaborate to enjoy the synergistic innovation benefits thereof or under other conditions (e.g. like fierce competition or low appropriability while expecting considerable adherent spillover) internalize development of complementary technology. In subsection 7.5.6, we recommend to further expand the conception of R&D activities to not only acknowledge that firms have certain engineering capabilities and knowledge, but also to introduce adherent spillover that, as we argued, can be an important disincentive for an agent to engage in collaboration.

After having implemented all these ameliorations, we have to acknowledge that a firm will not pick an arbitrary firm specialized in certain technological components, especially given the danger of externalities, spillover and opportunistic behavior.
In earlier models we had a refined partner assessment heuristics, but, as described in section 7.1, it was removed in a process of condensation to reduce variance and noise in results by increasing the selection force and making it pivotal on the 'eagerness to collaborate' as well as to isolate the cause of unexpected findings. As we have seen and discussed in subsection 7.3.2, our matching heuristic is really crude and has introduced the ill-appraisal effect (which we see as an artifact until we can prove otherwise) leading to more collaboration in some cases.
In reality, firms not only decide on the basis of the amendments by the potential partner, but certainly also (or perhaps even more) assess properties of the potential partner, e.g. the expertise of the firm and disciplines in which the firm is active, the history of collaboration and the financial health of that potential partner, et cetera. It is suggest to inspect the effects of reintroduction of the previously thought-out yardsticks in the partner selection heuristics of an agent.
An agent should however not just be able to assess with which agent to collaborate. With the proposed extension of the action options, an agent should furthermore be capable to decide whether and, if so, to whom R&D development is outsourced, from which agent certain technology will be bought. Such decisions of course also relate to the features of the potential candidates.

7.6 Tips for fellow-students designing a Neo-Schumpeterian model

As can be seen from the many shortcomings and recommendations, we think there is yet a lot to learn in the field of Neo-Schumpeterian modeling. Given the capabilities of Evolutionary Economics in explaining technological change, the sheer beauty of emergent behavior and the powerful tool that a Neo-Schumpeterian model can be in policy engineering, we would not find it surprising to see more Technology Management students (and scholars for that matter) using Neo-Schumpeterian models in a couple of years. As such, we see great use for a 'cooking book' for the design of a Neo-Schumpeterian model. Hereby we provide our contribution to such a cooking book in the form of several tips based on the experiences during our own research:

1. In experimental research, start with a properly considered theoretic framework and derive the operational model from that. Sure, this will be an iterative process. We however stress not to start out with elaborate experimenting with simulation model designs to later try to find or contrive a closely matching theoretic framework. The design of the simulation and operational models with the parameter space explorations and bug hunts take up a lot of time. After finding interesting simulation results meeting (properly ill-defined) presumed causal relationship or stylized facts, it is frustrating, if not endangering the quality of the research, to find out that there still are options or factors in the theoretic framework later established that have yet to be operationalized. Under time and resource constraints you might end up having to settle with this imperfect match.

2. Establish the properties of the various Neo-Schumpeterian model components in isolation. In writing the source code for each of the components, design degeneracy tests that allow inspection of effects on operationalized conceptual factors. Once the whole simulation model is up and running, it is often difficult to discern the (artificial) effects of the various model components on the emerging, aggregate results. As an additional advantage, it allows one to test the implementation, but, more importantly, to assess the consistency and adequacy of the model component in representing theoretic mechanisms. This enables the designer to prematurely reformulate the operational model components and thereby bolster the internal validity. Note that this relates to the first point, as the theoretic framework needs to be known in order to be able to do so.
3. Given the limited time and resources, the designer has to restrict the Neo-Schumpeterian model complexity. If the research goal is based on certain empirical findings or stylized facts, but the intention is not to establish a history-friendly model, it is important to isolate those facets of the empirical findings that are really relevant at an early stage, to thereby be able to limit the conceptual framework and operational model.
4. Be sure to consult your professors frequently during the establishment of the theoretic framework (which is likely to be a synthesis or derivation of existing theories) and the design of the operational model. Enjoy their experience, intelligence and know-how. As far as the hints on model components goes, listen carefully, but remain skeptic and investigate implications (also see point 2) as the field of Neo-Schumpeterian model-based economics is young and still heavily developing, and there is yet a lot to do.
5. In the end, dare to make choices in designing the operational model (and establishing the theoretic framework). Especially at this stage of development of the field, it is not possible to design the generally-agreed-upon, all-encompassing model for your research topic. If you make a wrong decision, which you cannot undo due to time and resource constraints, be aware that also your errors and sources thereof are valuable for the scientific community. To serve the cumulation of scientific knowledge, be sure to pinpoint and properly evaluate the shortcomings found and provide recommendations and ideas to overcome these issues.

Summary

In this research, we study the allegedly positive relationship between technological complexity and the propensity to collaborate in R&D as derived from differences in the inclination to collaborate in high-tech in comparison to non-high-tech sectors as found in empirical studies. At the outset, we decided to use simulation as research instrument and thereby use search on the Kauffman NK landscape as a metaphor for operational R&D. Preliminary investigation however had us doubt on the adequacy of this landscape search model and we therefore decide to evaluate the properties of landscape search in conjunction with testing the hypothesis.

First of all, we discuss the basic theoretic framework. We justify our choice to pick the Evolutionary Economic rather than the mainstream Neo-Classical Economic presumptions as starting point to explain economic change. In line with scholars active in the field of applied Evolutionary Economics, we opt for use of a Neo-Schumpeterian simulation model for experimental research. We elaborate on the premises of such a simulation model.
We then explain that, of the various specific economic theories to explain the collaboration propensity, we prefer the concise and conclusive Transaction Cost Economic (TCE) theory. Using the properties of R&D, we restrict and refine the TCE framework and adorn it with specific Strategic Management theories. We thus come to a comprehensive conceptual model in which we predict the collaboration propensity from technological complexity, the level of competition, complementarity and appropriability. The basic idea is that firms are willing to collaborate if the detrimental effects of non-appropriable spillover are outweighed by the increase in (synergistic) innovation performance achieved due to the contribution of complementary technological knowledge and capabilities by the collaborating firm. If the complexity is higher, technological uncertainty is higher and the effect of complementary knowledge is more significant, so firms are more inclined to collaborate. Dynamic inefficiencies and hence the effects of non-appropriable spillover as well as innovation performance improvement are amplified by competition.
In order to emphasize our interest in the effect of complexity and to serve analytical tractability in the final results, we do not describe and use the configurations of factors required to properly stylize high- and non-high-tech sectors, but rather the level of the factors expected in high- and non-high-tech sectors and the intermediating effect of each of those factors in isolation on the relationship between complexity and collaboration propensity.

We conduct a small survey of Neo-Schumpeterian models that are used to study R&D collaboration and also of technology landscape search models that are used to model operational R&D activities. After evaluation of the properties, we decide to design a Neo-Schumpeterian model from scratch, but rely on the much-praised Kauffman NK landscape to model operational R&D (collaboration).

Our Neo-Schumpeterian model has a population of agents following a certain R&D strategy (possibly collaborative) and rewards these agents according to their R&D performance. An evolutionary framework of entry and exit pivotal on the R&D performance drives the emergence of situational locally-superior R&D strategies and thereby the collaboration propensity.
The Kauffman technology landscape search is introduced to model operational R&D activities of the agents. We base our operationalizations of factors in our TCE framework direct or indirect on the concepts introduced with this technology landscape.
We use the number of interdependencies (intricacy) as the operationalization of the factor complexity. The search capabilities of the agents are furthermore confined to a patch on that technology landscape to meet the Simonian behavioral limitations of agents. The breadth of this patch is the operationalization of the factor complementarity. Agents can bring the technologies they develop to a shared demand market at which the technology fitness is translated into payoff. The market

return is used to operationalize the level of competition. Agents also 'patent' the technologies they bring to the market, which then protects the patent-owner(s) against opportunistic use of spillovers (obtained through collaboration) and of externalities (obtained through reverse engineering of technologies on the market) by assuring 'monopolistic' payoff for some time. We use the patent duration to operationalize the factor appropriability.
We furthermore endow agents with an R&D strategy that is used in a matching algorithm to determine whether and -if so- with whom to undertake a collaborative R&D project. Since the R&D strategy determines the eagerness to collaborate, and the innovation performance determines the payoff, the capital stock is an expression for the success of the strategy. We complement the financial module with costs of R&D and we thus introduce a natural evolutionary deselection mechanism by means of 'bankruptcy' of an agent. We furthermore introduce a Herfindahl-index based entry intensity, which has agents enter that (imperfectly) imitate the R&D strategy of relatively wealthy agents. We thereby introduce evolutionary novelty and variation.
The evolutionary framework 'trains' the population of R&D strategies according to their market performance, which in turn depends on the techno-economic specifications spanned by the adorned TCE factor operationalizations. We subsequently measure the collaboration propensity induced by the evolutionary conditioned R&D strategies.
Following the rationales in the TCE model, we formulate hypotheses on the effect of the operationalizations of the TCE factors on the emerging collaboration propensity.

In line with our research design, we run simulations for a two-dimensional space of the operationalization of one of the factors in conjunction with the operationalization of complexity. We find that part of our simulation results contradict our operational hypotheses.
In line with theory, the collaboration propensity increases with complementarity. The collaboration propensity reflects the innovation performance augmentation achievable by collaborating. However, in contrast to expectations, collaboration propensity drops in complexity, caused the manifestation of the Kauffman complexity catastrophe which squeezes the achievable performance augmentation. If complexity is low, the artificially high collaboration propensity stems from 'concealed buying' of complementary components induced by absence of market governance as R&D strategy option. We also find that ill-appraisal of the project amendments suggested by the potential collaborators yields a collaboration propensity that cannot be justified for by the actual eventually achieved performance increase.
We see preliminary expectations confirmed in that our model lacks spillover due to our overly simplistic conception of technology and innovation capabilities. Rather than stimulating collaboration by hampering opportunistic use of spillover, appropriation allows soloist early movers to build up resilience for market shocks. In case of externalities, appropriation however stimulates collaboration as agents then circumvent patents, get top-fit technology by exploiting the head start and since patents form a disincentive for externality-opportunism. In contrast to expectations, appropriation instruments are especially effective in protecting complex technology as it is difficult to change the delicate combination of technological components.
We discover that collaboration propensity increases with the level of competition. This is in line with expectations, after all, since (non-adherent) spillover is absent (and hence does not deteriorate dynamic efficiency), the advantage of performance augmentation realized by collaborating becomes more crucial in survival.
We see that the complexity catastrophe squeezes the performance augmentation with an increase in complexity, and thereby the collaboration propensity, in all three cases.

We interpret the simulation findings in the realm of the TCE model and elaborate on the discrepancies in preliminary theoretic expectations and simulation results, both the factors in isolation, as well as in conjunction in an evaluation of the high- and non-high-tech sectors. If we translate the operational shortcomings producing these discrepancies into restrictions to our TCE model, we see

that the findings in fact are conform the predictions of that restricted TCE framework.
In order to contribute to the scientific art of building Neo-Schumpeterian models, we then elaborate on the cause of the shortcomings, notably the oversimplification of operational R&D activities and the fact that the development of the landscape fitness distribution for changes in complexity does not reflect that of technological performance. We provide ideas on how to ameliorate the technology landscape and meet more dimensions of the definition of complexity.
We take it one step further even and revert to the original Neo-Schumpeterian model premises. We then see that the operational model also falls short in reflecting the industry development as we do not include firm activities like specialization, segmentation and standardization, which also closely relate to the development of the technological regime and the technological complexity firms face.
We evaluate the implications for our understanding of R&D collaboration under technological complexity. We see that, despite these shortcomings, the model designing exercise and our critical appraisal of the flaws gained us a profound understanding of the (dis)advantages of collaborating in R&D and the role of the operationalized TCE factors therein. Based on this profound understanding, we formulate an integrated framework of rationales for collaborating in R&D under complexity, which in fact is highly conform with the TCE model and underpins the main hypothesis, but which is certainly richer and is firmly buttressed with operational explanations.

Finally, we provide recommendations for further research concerning, a.o., adjusting and deepening the technology landscape search and the agent R&D model and contesting the established adorned TCE framework. We also provide tips for fellow-students to take to heart in designing a Neo-Schumpeterian model.

Appendix A

Complexity catastrophe

Kauffman (1993, p.52) describes complexity catastrophe as follows: 'as complexity increases, the heights of accessible peaks fall toward the mean fitness'.

Let us pick $V = 20$ technologies at random from $W = 50$ different landscapes for $N = 40, 60, \ldots, 200$ and (since $K < N$) $K = 5, 25, \ldots, (N-15)$. For each randomly picked starting point T_{vwnk} we have a single agent with full expertise $|E| = N$ optimize the technology to T^*_{vwnk} with fitness $F(T^*_{vwnk})$. We thus get the following distribution:

$$\{n, k, \{F(T^*_{11nk}), \ldots, F(T^*_{V1nk}), F(T^*_{12nk}), \ldots, F(T^*_{V2nk}), \ldots, F(T^*_{VWnk})\}\} \quad \text{(A.1)}$$

In figure A.1 a boxplot of the fitness values $F(T^*_{nkvw})$ per pair $\{n, k\}$ is shown. In figure A.2 a barplot of variance of these fitness values per pair $\{n, k\}$ is shown.

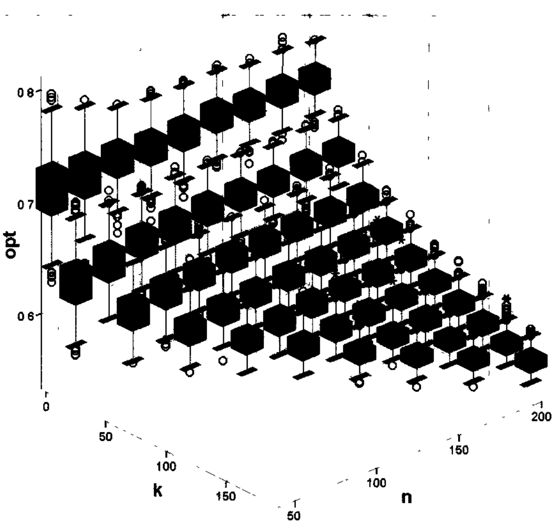


Figure A.1: Boxplot of the fitness of optima found for 20 draws from 50 landscapes per K and N pair

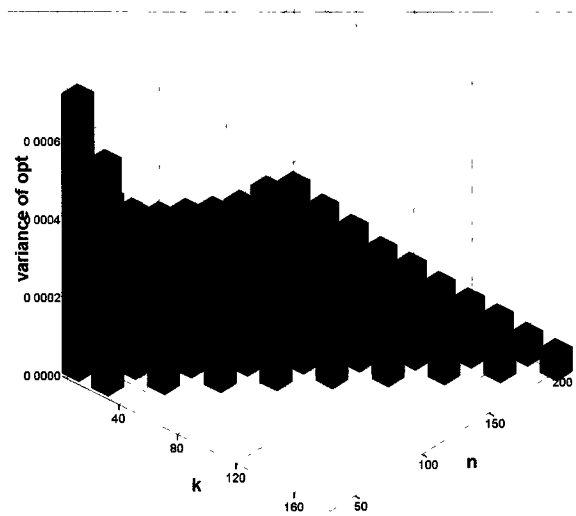


Figure A.2: Barplot of the variance of the fitness of optima found for 20 draws from 50 landscapes per K and N pair

We see that the fitness values and the variance quickly drop in K (hence the name 'complexity catastrophe'). As the fitness of each element itself is an average of K fitness contributions, there is a strong regression to the mean. We see that the variance decreases for an increasing N (for fixed K), but not the fitness values. Due to the properties of having individual fitness values drawn from the uniform distribution, the fitness of the obtainable optimum more or less stays the same, but as there are more elements involved (N), the variance decreases. These results confirm the findings of Kauffman (see p.56).

Appendix B

Actual achievable innovation performance augmentation

In order to understand the underlying incentives for collaboration, let us look at the effect of collaboration on the global fitness of the local optimum obtained.

We generate $V = 100$ pairs of a starting technology and an instance of a technology landscape (with $N = 72$) for a certain level of complexity K. We then let a single agent with expertise E_1 with breadth $|E_1| = E$ improve each of those technologies (following the Simonian fitness $F(T, E_1)$) and we register the global fitness values obtained as F^s_{KEi} $(i = 1, \ldots, V)$. We then let two agents with expertise with breadth $|E_1| = |E_2| = E$ (and fields of expertise such that overlap (complementarity) is as small (big) as possible) collaboratively improve the technologies (hereby both following $F(T, E_1 \bigcup E_2)$) and register the global fitness values as F^c_{KEi}. We can then calculate the average obtained fitness values $\bar{F}^c_{KE} := \sum_{i=1}^{V} F^c_{KEi}/V$, $\bar{F}^s_{KE.}$ and the difference $\bar{D}_{KE} = \bar{F}^c_{KE} - \bar{F}^s_{KE}$. We now run this experiment for $K = \{5, 15, \ldots, 65\}$ and $E = \{10, 20, \ldots, 60\}$ and thus get three distributions $\{E, K, \bar{F}^s_{KE}\}$ plotted in figure B.1, $\{E, K, \bar{F}^c_{KE}\}$ plotted in figure B.2 and finally $\{E, K, \bar{D}_{KE}\}$ plotted in figure B.3.

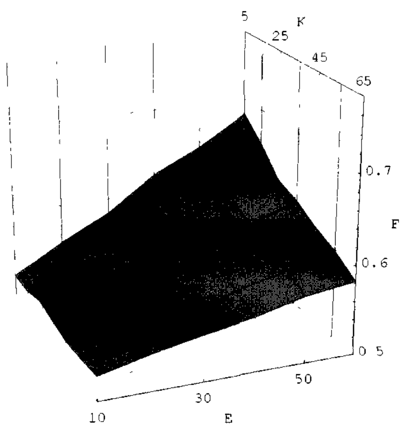


Figure B.1: Plot of distribution $\{E, K, \bar{F}^s_{KE}\}$

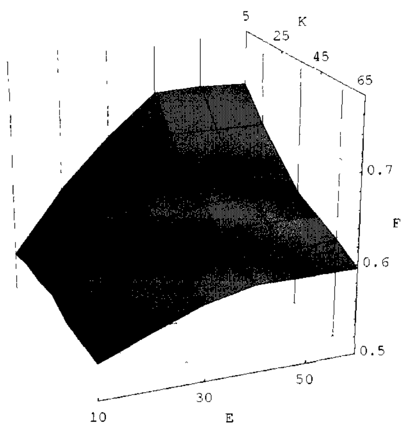


Figure B.2: Plot of distribution $\{E, K, \bar{F}^c_{KE}\}$

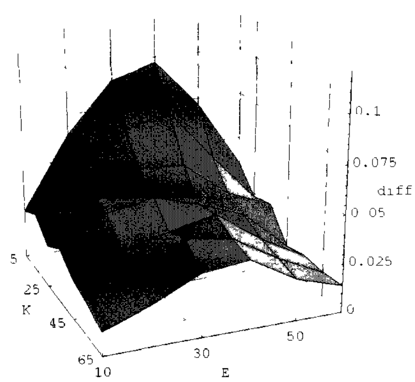


Figure B.3: Plot of distribution $\{E, K, \bar{D}_{KE.}\}$

From figure B.3 we see that collaboration yields fitter technologies (since $\bar{D}_{KE.} > 0$ for all K and E considered), in general, but what especially strikes us is the parabolic curvature! Note that the contribution of the collaborator consists of an increase in the accuracy of the fitness assessment (and thereby increasing the chance of selecting globally fitter (focal) technology) and in the fitness improvement by following a broader scope of control during search. From figure B.3 we establish that if agents are both highly specific (E close to zero) or both generic (E close to N), the contribution of a collaborator in terms of (additional) fitness is small.
We conclude that $E \xrightarrow{\cap} \bar{D}_{KE}$ and $K \xrightarrow{-} \bar{D}_{KE}$.

So, we see that collaboration yields fitter technology and we also refer to this phenomenon as the increase in innovation performance, or the innovation performance augmentation by collaboration.

Appendix C

Collaboration preference due to ill-appraisal of amendment

To understand when agents approve collaboration, i.e. accepts a collaboration proposal, we investigate the matching criterion as described in section 5.3. Recall that the primary agent appraises a collaboration project 'proposal' based on $\Delta_{ij} = F(T_i^P \otimes_{E_j} T_j^*, E_i \bigcup E_j) - F(T_i^P, E_i)$. If Δ_{ij} is below the threshold value δ_i, agent i will not even consider working with agent j, but if it exceeds that value, agent i is willing to collaborate. We now wonder what the distribution of Δ_{ij} is for various values of K and E to get an impression how often collaboration is preferred for certain threshold values.

We are now going to inspect this Δ_{ij} for the values $K = 5, 15, \ldots, 65$ (with $N = 72$) and $E = 10, 20, \ldots, 60$. For each pair $\{E, K\}$, we determine Δ_{ij} for $V = 100$ different landscapes with E and K as specified. For each landscape, we generate two large sets of technologies, instantiate two agents (agent 1 and 2) each with an expertise of E (such that the fields of expertise have as few elements in common as possible) and give each of them the fittest technology from one of those sets as their top-technology (T_1^* and T_2^*). Next, we generate a starting technology T^I and have agent 1 determine T_1^P. As we know $T_1^P = T^I \otimes_{E_1} T_1^*$ if $F(T^I, E_1) < F(T^I \otimes_{E_1} T_1^*, E_1)$ and $T_1^P = T^I$ otherwise. We then have agent 2 suggest an improvement $T_2^P := T_1^P \otimes_{E_2} T_2^*$ and register $\Delta_{12} = F(T_2^P, E_1 \bigcup E_2) - F(T_1^P, E_1)$.

As we do this for $V = 1, \ldots, 100$ for various values of E and K, we obtain $\{E, K, \{\Delta_{121}, \ldots, \Delta_{12V}\}\}$ which is depicted in figure C.1 in the form of a boxplot (rather than a scatter-plot).

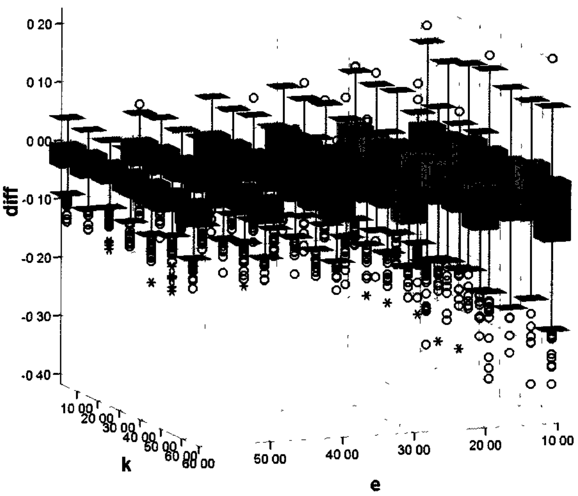


Figure C.1: Boxplot of $\{E, K, \Delta_{12V}\}$

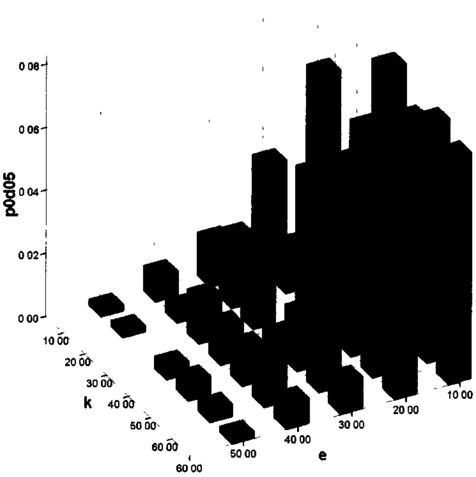


Figure C.2: Probability of Δ_{12} exceeding $\delta = 0.05$, based on $\{E, K, \Delta_{12V}\}$

We do see that the variance increases with E and actually becomes considerable for $E = 10$. There is a slight decrease in median, but still the 95% whisker point exceeds that of lower E values. This means that there are more, higher Δ values, which implies -given the same δ threshold- agents are more likely to prefer collaboration than for lower E values! We see this confirmed in figure C.2 depicting the probability p of $\Delta \geq 0.05$. The probability increases with E decreasing. So, this preference for collaboration hence actually stems from an 'ill-appraisal' of the real contribution of the collaborator due to low breadth of expertise!

Appendix D

Exploitation of Head Start

In order to understand the underlying incentives for collaboration if there is reverse engineering, let us compare the global fitness of the solo and collaboratively obtained optima of both reverse engineered and freshly invented technology.

Let us first define $F^{Sim}_{\cdot\cdot}$ and $F^{Gl}_{\cdot\cdot}$ as the Simonian and global fitness respectively, $F^{\cdot}_{C\cdot}$ and $F^{\cdot}_{S\cdot}$ as the fitness of the optimum obtained by collaborating and working solo respectively, and $F^{\cdot}_{\cdot I}$ and $F^{\cdot}_{\cdot R}$ as the fitness of the optimum obtained by starting from a freshly invented or a reverse engineered technology respectively. Finally, $F^{Sim}_{\cdot}$ and $F^{Gl}_{\cdot}$ are the Simonian and global fitnesses of the technology with which an innovation trial starts, where $T^{\cdot}_{I}$ and $T^{\cdot}_{R}$ are the invented and the reverse engineered technology respectively.

Let us first get a picture of the outcome of innovation in case an agent reverse engineers and in case an agent does an invention.
First of all, we instantiate a landscape with a particular K (and N) and we take the globally fittest technology T^R and a random technology T^I out of a set of size X of randomly generated technologies. We subsequently initialize two agents with breadth of expertise E, but we now allow E_1 and E_2 to overlap to reflect the reality in the simulation model. So, both fields of expertise are a patch of size E starting at a random index (and wrap around at N of course). We then let one agent optimize both T^I and T^R, thus producing $F^{\cdot}_{SI}$ and $F^{\cdot}_{SR}$ and we then let the two agents collaboratively optimize both T^I and T^R, thus producing $F^{\cdot}_{CI}$ and $F^{\cdot}_{CR}$. We repeat this for L landscapes. We also take the values $K = 15, 35, 55$ and $E = 20, 40, 60$ to obtain the data $\{K, E, \{F^{\cdot}_{\cdot}[l], F^{\cdot}_{\cdot\cdot}[l]\}\}$ for $l = 1, \ldots, L$.

In figure D.1, we show six panels for different pairs of K and E consisting of two parts. The left-hand part contains boxplots of F^{Sim}_{I}, F^{Gl}_{I}, F^{Sim}_{SI}, F^{Gl}_{SI}, F^{Sim}_{CI} and F^{Gl}_{CI}, in that order. The right-hand part contains boxplots of F^{Sim}_{R}, F^{Gl}_{R}, F^{Sim}_{SR}, F^{Gl}_{SR}, F^{Sim}_{CR} and F^{Gl}_{CR}, in that order.

Not surprisingly, we see that indeed the fitness of the starting point is higher in case of reverse engineering than is in case of invention, i.e. $F^{Gl}_{R} > F^{Gl}_{I}$ and also $F^{Sim}_{R} > F^{Sim}_{I}$. We also notice that the $F^{Sim}_{\cdot\cdot}$ values are generally higher than the $F^{Gl}_{\cdot\cdot}$ values. These discrepancies are caused by the higher variance (and large range) of fitness values. What is more interesting is that the Simonian fitness of solo obtained technologies is actually higher than the Simonian fitness of collaboratively obtained technologies, i.e. $F^{Sim}_{S\cdot} > F^{Sim}_{C\cdot}$, while actually the opposite is true if we look at the global fitness, i.e. $F^{Gl}_{S\cdot} < F^{Gl}_{C\cdot}$. So, the additional expertise helps to better valuate the fitness and adjusts it to be closer to the real, global fitness value, which, in general, is lower, but the drop in Simonian fitness that collaboration brings about is misleading because getting another agent to collaborate in fact brings about a jump in *global* fitness!
From the perspective of a Simonian agent, collaboration hence brings about a decrease in (Simonian) fitness of optima, while in fact it would improve the global fitness of optima! Remind that in our model, agents are insensitive for the actually achieved innovation performance augmentation or so, but rather are -at population-level- weeded out on their performance that is based on global fitness. So, indeed, collaborative behavior can emerge as it is (sufficiently) beneficial in some cases. As the global fitnesses obtained hence really matters, we will now focus on the differences for the two different sources of the starting technology. We see that the difference between the obtained global fitness when starting off from a reverse engineered technology and when starting off from a freshly invented technology is not particularly high, i.e $F^{Gl}_{\cdot R} - F^{Gl}_{\cdot I}$ is small, and that this holds for

both solo as well as collaboratively conducting innovation. We see that this difference even further diminishes if K and/or E increases.

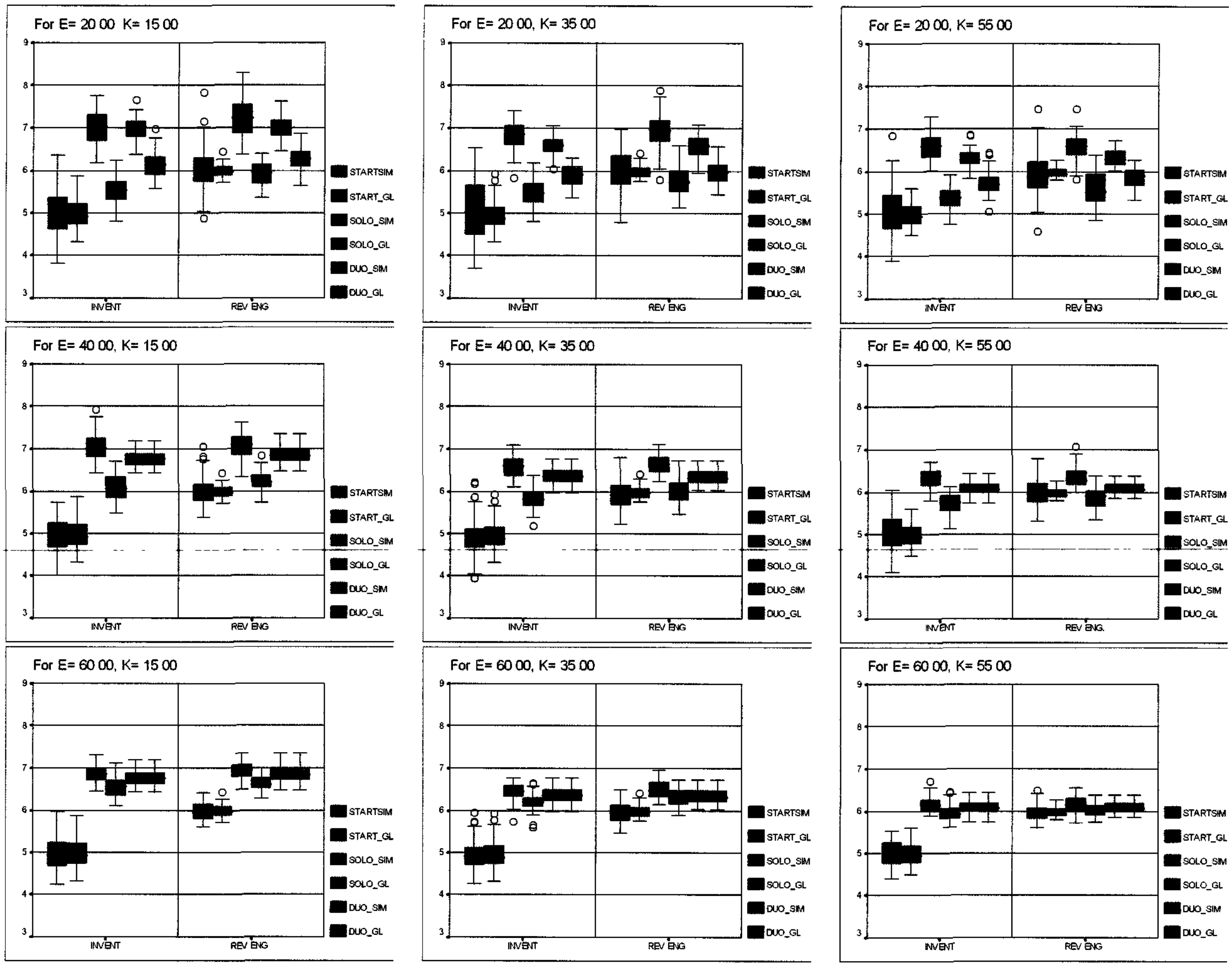


Figure D.1: Boxplots of various fitness values achieved by collaborating and working solo on innovating reverse engineered and invented technology, for various values of E and K

Let us now check whether collaboration indeed 'exploits the head start'. We will do this by checking whether really higher or more-or-less equally fit technologies are obtained by working solo or collaborating if the starting technologies are reverse engineered or freshly invented.
Figure D.2 contains six panels (again for the aforemention values of K and E) with scatterplots of the global fitness of the starting technology versus the maximum obtained optimum, i.e. $\{F_x^{Gl}, \max F_{yz}^{Gl}\}$. We hereby plot the scatter symbol in red (blue) if the starting technology is freshly invented (reverse engineered) and pick a circle (triangle) as symbol if the optimum is obtained by working solo (collaborating). To get a somewhat clearer picture, we have increased the set size X, so that reverse engineered technology has a notably higher global fitness and that the cloud of blue symbols has shifted to the right.

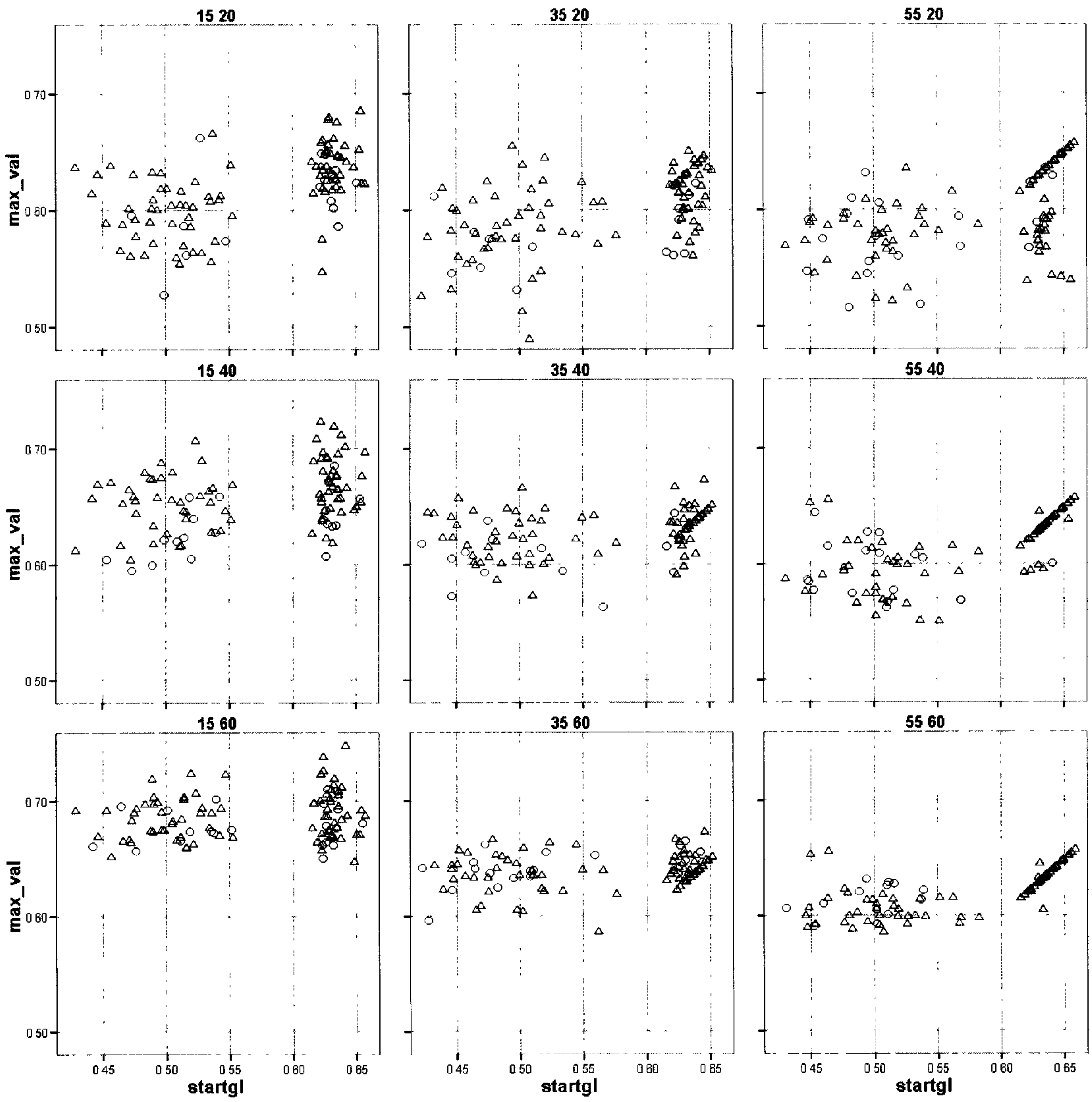


Figure D.2: Maximum global fitness obtained by working alone (circle) or by working together (triangle), both for fresh inventions (red symbols) and reverse engineered technology (blue symbols).

Firstly, we see that most of the symbols are triangles, both when reverse engineering and when inventing, so, working together generally yields a fitter optimum.
Secondly, although it was not immediately obvious from figure D.1, we now immediately see that the blue symbols are generally plotted higher in the figure such that the global fitnesses is predominantly higher. So, following the best possible strategy (i.e. either working solo or collaborating, as long as it yields the fittest optimum), starting from a reverse engineered technology indeed yields fitter technology than starting from a freshly invented technology.

In figure D.3, we plot the fitness of the starting technology and the difference between the fitness of the optimum when working collaboratively and working solo, we see that this difference is predominantly positive, irrespective of whether the starting technology is freshly invented (circle) or reverse engineered (triangle). The color of the symbol is related to the fitness of that 'the best optimum' (i.e. either the optimum of working solo, or the optimum of working together).

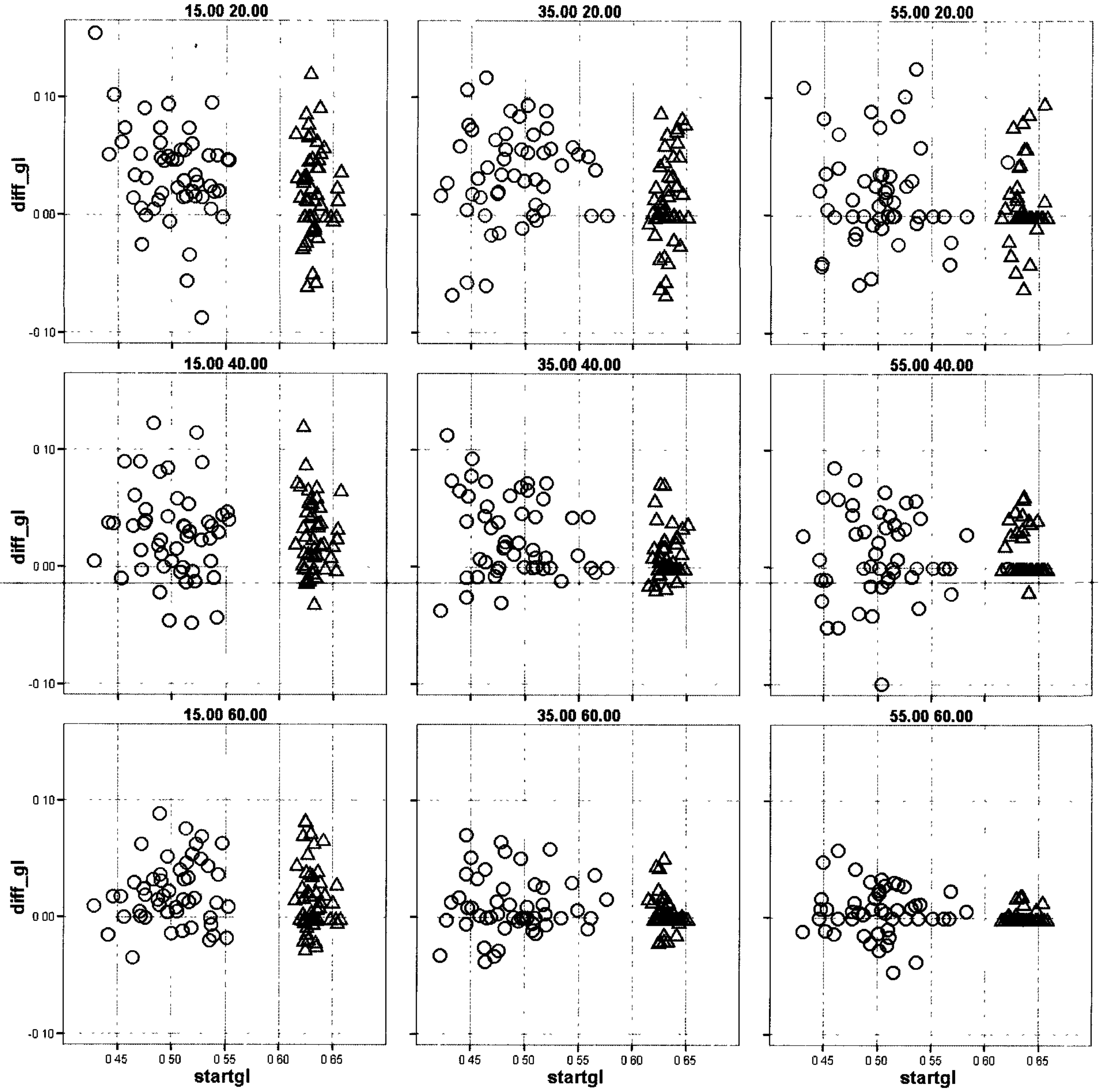


Figure D.3: Difference of global fitness obtained by working alone or by working together, both for fresh inventions (circles) and reverse engineered technology (triangles).

So, we conclude that there is a head start advantage and (from a fitness point-of-view) this is indeed exploited best if collaborating. We also see that this advantage can be considerably large even if the starting technology is reverse engineered!

Appendix E

Circumventing patents on reverse engineered technology

Reverse engineering a technology T^m on the market and then improving it according to own expertise (and Simonian fitness assessment) would eventually yield a technology T^r that is likely to infringe the patent on technology T^m. In this appendix, we study when collaborative innovation does circumvent the patent on a reverse engineered technology while solo innovation does not. We expect both the intricacy K and breath of expertise E to play an important role.

If E is narrow, agents have only few elements to manipulate to escape the patent neighborhood of technology T^m. We therefore expect the Hamming distance of original technology T^m and eventually produced technology T^r to be low. On the other hand, if the breadth of expertise is narrower, the Simonian fitness is less accurate, which in turn creates its own different basin of attraction likely to be different from the basin of attraction when the technology was first developed. So, in case of narrow expertise, the reverse engineering agent's perceived basin of attraction is also more likely to yield an escape from the developer's perceived basin of attraction. Thereby, the Hamming distance $H(T^m, T^r)$ increases. If E is broad, agents have many elements to manipulate to escape the patent neighborhood of technology T^m, so we expect the Hamming distance between T^r and T^m to be high. On the other hand, as the Simonian fitness assessment is more accurate, the shift in basin of attraction of the developer to the reverse engineering agent is moderate and the Hamming distance $H(T^m, T^r)$ is expected to be relatively low.
We now see two counterbalancing phenomena. On the one hand, we expect the Hamming distance $H(T^m, T^r)$ to increase in the number of elements E available for manipulation as there are more elements to manipulate. On the other hand, we expect the innovation trail length to be shorter due to a better assessment of the true fitness of both the original developer and the agent reverse engineering the technology, so they are increasingly likely to face more or less the same basin of attraction. We have to bear in mind that the overlap in the fields of expertise is low in expectation if the E is low. Thereby, the latter argument looses in strength.

The effect of the level of complexity K is straightforward. The ruggedness of the landscape as tuned by K affects the innovation path length and hence the Hamming distance $H(T^m, T^r)$. Agents are caught in a local optimum sooner when the complexity is higher. We expect this to be especially true when the breadth of expertise is moderate to high, and less when it is low. This of course is caused by the Simonian fitness assessment that is then less accurate and spans its own basin of attraction.

Collaboration is an obvious way to expand the expertise by simply joining the fields of expertise. To get an understanding of the true value of collaboration in circumventing patents of a reverse engineered technology, we will inspect the Hamming distance in case an agent improves a reverse engineered technology solo and in case two agents improve that same technology in collaboration.

We first instantiate a landscape with the appropriate level of complexity K. We create a market $\mathbf{T}^m$ of size M by having $A = 15$ agents with breadth of expertise E (but different fields) doing $W = 100$ inventions (a random starting point) and either improving them solo or in collaboration (which is random). In order not to further complicate the fundamental test setting, we have decided at random which agents work solo and which agents collaborate. We also pick two agents (agent 1 and 2) and let them keep record of their Simonian top-fit technology during the formation of the market.

We then pick a technology T^r at random from this market. We have agent 1 consider substituting components of its top technology T_1^* into T^r and, based on own fitness assessment, which technology

T_s^b it will hence use to start the R&D project with. Agent 1 subsequently improves this technology solo to obtain technology T^s. We then determine the minimum distance $H_s = H(\mathbf{T}^m, T^s)$ to the technologies already on the market.
We then have agent 1 and 2 collaborate, and they follow the procedure described in section 5.3 to come to the project starting technology T_c^b. At this stage, this means that agent 2 substitutes the components in T_s^b within its own field of expertise E_2 with components from its top technology T_2^* to create the starting technology T_c^b. The agents now together improve this technology to obtain T^c. We then determine the minimum distance $H_c = H(\mathbf{T}^m, T^c)$ to the technologies already on the market.
Using H_c and H_s, we determine P_x. Hereby P_x equals 1 only if $H_d > h$ while $H_s \leq h$ and hence is a code for whether working together would really yield the advantage that it helps circumventing a patent that an agent alone would otherwise not. We now repeat this procedure for (a small number) R times (i.e. R random reverse engineered starting points of the same market $\mathbf{T}_m$). We will do this for L landscapes.
We repeat this experiment for a range of values for K and for E and hence obtain the distribution $\{k, e, \{H_s[r,l], H_d[r,l], P_x[r,l]\}\}$. We calculate the mean over r and l and get the probability that collaboration indeed helps circumventing the patent when working solo does not.

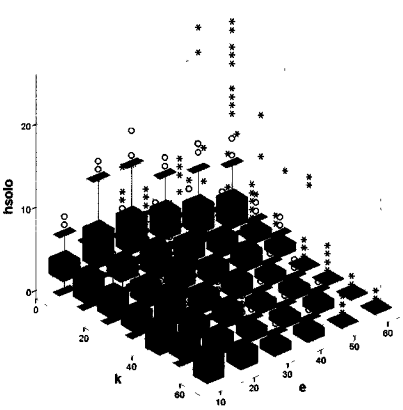


Figure E.1: Boxplot of $\{E, K, H_S\}$

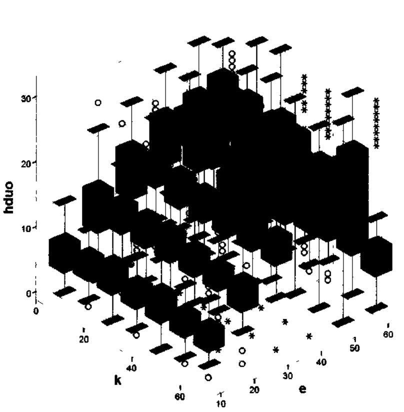


Figure E.2: Boxplot of $\{E, K, H_D\}$

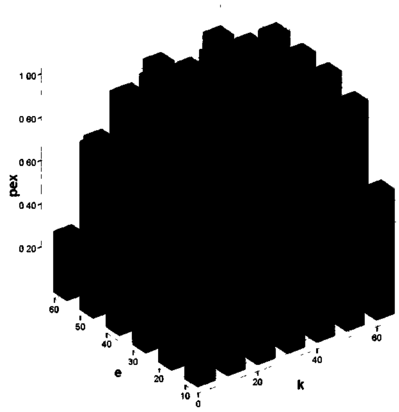


Figure E.3: Barplot of $\{E, K, P_X\}$

In figure E.1, we present a boxplot of $\{k, e, H_s[r,l]\}$ and in figure E.2, we present a boxplot of $\{k, e, H_d[r,l]\}$. We immediately see that the differences in outcome are considerable! If K is low and E is arbitrary or if E is low and K is arbitrary, agents working solo have a considerable chance to circumvent the patent alone. For other combinations, agents working solo have only a small chance while agents collaborating nearly always circumvent the patent. We see from figure E.3 that collaborating indeed (very) often has the advantage that it circumvents the patent while working solo would not.
Additional tests have shown that especially the compulsory substitution of components by agent 2 greatly contributes to the shift compared to the original technology.
One might ask why agents then do not collaborate all the time. This of course relates to the global fitness of the optima thus reached and innovation performance augmentation obtained for the collaborators.

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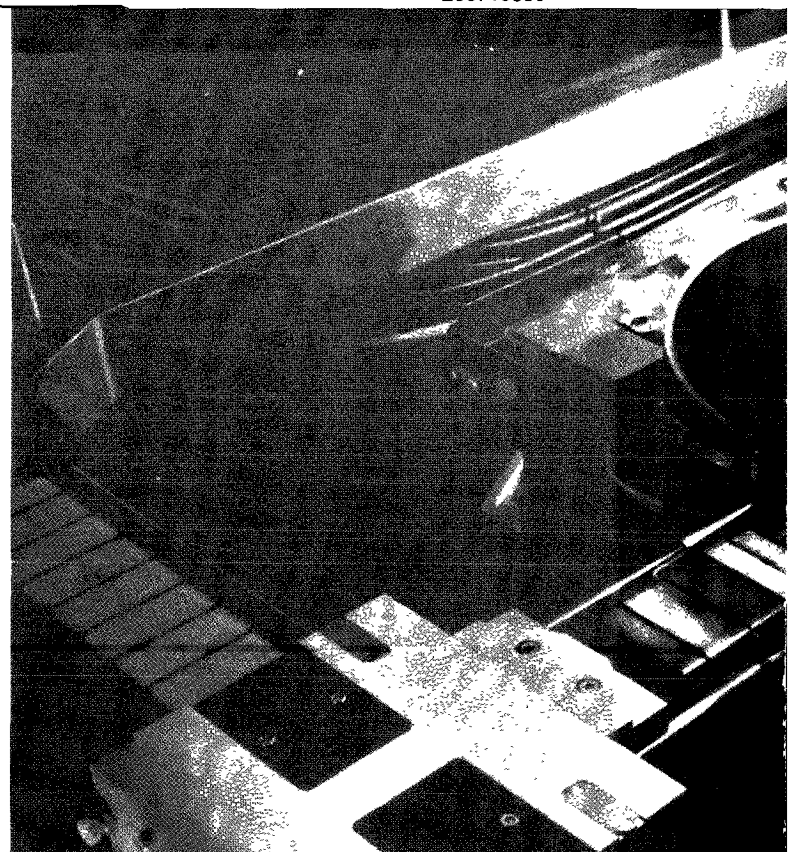
June 2001



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