Path Dependence and the Environmental Context

An Inquiry into the Effects of Environmental Complexity and Turbulence on Path Dependence in Organizational Learning

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“Organizational learning resembles a changing delta of meandering flows, some of which get blocked, while new flows emerge and others get reinforced.”

(Berends & Lammers, 2010:1059)

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N	number of environmental dimensions
K	environmental complexity
τ	scope of environmental change
x	frequency of environmental change
p_a	speed of learning from the code
p_c	speed of learning by the code
p_{expl}	speed of individual learning
avgScoresRaw	average learning success of organizational members
orgScore	learning success of organizational code
uniqueAgents	number of different beliefs in the organization
heterogeneity	heterogeneity of beliefs in the organization

1 Introduction

1.1 Problem Statement

This dissertation sets out to increase our understanding of the effects of the environmental context on organizational path dependence.

Path dependence theory has its roots in the famous QWERTY case study of Paul A. David (1985). The prominent case investigated the competition between different keyboard technologies and proved that an inferior technological standard can achieve market dominance crowding out better solutions available. With this result, David challenged the central belief of mainstream economics that markets guided by the 'invisible hand' produce efficient outcomes. Path dependence theory showed that market outcomes neither have to be efficient nor are they necessarily easily corrected. Rather, path dependence research demonstrates that despite initial flexibility and indeterminacy special properties of these processes can lead to stable inefficient results. Far from the ahistoric position of mainstream economics, QWERTYnomics claims that history matters. Only timing and sequence of events determine for which of the many possible outcomes a process will settle. Therefore, path dependence evolves as a consequence of a process' own history. The reason for this can be found in self-reinforcing effects which form the heart of path-dependent dynamics. Small events can thus become reinforced, exerting a huge unforeseen influence on the process' outcome. In a theoretical model, Arthur (1989) showed that self-reinforcement is the defining property of path-dependent processes. A common example for a mechanism which leads to self-reinforcement is increasing returns to scale. In case of the QWERTY keyboard, for example, a higher production volume distributed the fixed costs across a larger number of units. These decreasing cost conditions made a further increase of the production volume more attractive therewith closing the feedback loop (David, 1985:335; Vergne & Durand, 2010:743).

It is only in a regime of increasing returns that small events in the market process are not averaged away but become magnified, finally pushing the process into an inflexible, inefficient end state called lock-in.

To address persistence in organizations, Sydow, Schreyögg, & Koch (2009) elaborate a theory of organizational path dependence in which they build on the findings derived from research on technological paths and extend these into an organizational context. Based on the dynamics of internal organizational processes, their framework specifies the self-reinforcing effects at work in organizations. Whereas organizational path dependence theory also postulates positive feedback as the central triggering element of path dependence, self-reinforcement in organizations goes beyond the focus on utility calculus and individual decision making which we encounter in the increasing returns ruling the development of technological paths (Sydow, Schreyögg, & Koch, 2009:694). Self-reinforcement in organizations involves the institutional settings of organizations as systems of interconnected individuals. The four self-reinforcing mechanisms identified by Sydow, Schreyögg, & Koch (2009:698-701) have the potential, alone or in combination, to drive path-dependent developments in organizations.

Path dependence of single organizations involves dealing with persistence at the micro level of organization resources, capabilities, and strategies (Vergne & Durand, 2010:740). Clearly, path-dependent processes must be considered to be embedded in specific institutional contexts or environments. However, we lack knowledge on how the embedding context influences the unfolding of self-reinforcing processes (Koch, Eisend, & Petermann, 2009:67; Sydow, Schreyögg, & Koch: 2009:701). In the analysis of path dependence phenomena, the context has so far played a mostly implicit role (Koch, Eisend, & Petermann, 2009:67-68).

In Arthur‘s (1989) model, the context hides in several factors which are exogenous for the modeled agents, for example the technologies and their return functions. Other contextual conditions, such as the assumption of perfect information, are simply considered fixed. North (1990:95) already criticizes Arthur’s technological story, despite elaborating on the role of increasing returns, for not dealing with the environmental characteristics which breed path-dependent phenomena. He claims that Arthur’s (1989) model should rather be seen not merely as one of competing technologies but of competing organizations which represent these technologies. Consequently, the outcome of the modeled process not only expresses the characteristics of the technologies but also specific properties of their organizational context (North 1990:94).

In North‘s (1990) analysis of the path-dependent development of economic institutions, two forces are propounded as guiding the path of institutional change: increasing returns and imperfect markets characterized by transaction costs. North (1990) claims that in perfect markets, despite increasing returns, there would be no divergent paths, nor would we encounter long-term inefficient performance. Without enhancing contexts, increasing returns no longer impose a danger of creating suboptimal outcomes. The costs of transacting and incomplete information feedback create a complex environment which, for the agents, is difficult to decipher (North, 1990:95-96). Even if North (1990) therewith acknowledges the importance of contextual characteristics for path-dependent processes, in his study, complex environments are merely a necessary precondition for path dependence to occur (Koch, Eisend, & Petermann, 2009:68).

In his analysis of path dependence in political systems Pierson (2000) argues in a similar direction. He considers the inherent murkiness of the political environment to enhance path-dependent processes and to increase the likelihood for organizations (in this case formal political institutions) to become locked in. Complexity of organizational goals and opacity of the causal links between actions and consequences create a context which is especially conducive to increasing returns processes (Pierson, 2000:257). Even if Pierson makes an important point for the relevance of environmental characteristics for path-dependent dynamics, he fails to give a precise account of the impact of particular contextual factors. His analysis deals with a large number of contextual features leaving the specific causal relation between single contextual features and the unfolding dynamic underexplored (Koch, Eisend, & Petermann 2009:68). Sydow, Schreyögg, & Koch (2009:701) also point out that it is necessary to clearly differentiate between self-reinforcing mechanisms and the enabling context. Pierson’s analysis lacks such a precise specification of contextual features and self-reinforcing mechanisms. For example, power asymmetries as an important characteristic of organizational arenas, in his analysis seem to develop their own self-reinforcing pull (Pierson, 2000:259). These deficiencies point to a research approach in which the isolated influence of specific contextual features on particular self-reinforcing effects in organizations can be tested.

We consider complexity and turbulence of the organizational environment to be the most relevant features to explore. In organization theory, environments are often categorized in terms of their complexity (Sharfman & Dean, 1991:684; Burton & Obel, 1998:167; Suarez & Oliva, 2005:1019). Generally speaking, complex conditions can be described as a high number of elements which interact in a non-simple manner (Simon, 1962:648). Environmental complexity has not only been acknowledged as a central environmental feature in organization theory, it also plays an important role in the aforementioned approaches to path dependence. Organizational goals, social relationships, market requirements, regulations, many elements of the organizational environment and their interrelations contribute to its complexity. Environmental complexity is therefore a super-ordinate characteristic which is able to describe a variety of environments. This may also be the reason why both North (1990) and Pierson (2000) use it to describe the conditions created in markets with transaction costs and incomplete information or the murkiness of political arenas.

The effects of complexity on path dependence were analyzed by Koch, Eisend, & Petermann (2009) in an experiment on individual decision making. Their results illustrate that complexity significantly impacts the probability of lock-in. Still, the atomistic setting in which each individual decides independent of the behavior of others overlooks other important aspects which must be considered when dealing with organizational path dependence. In organizational surroundings path dependence is the result of an interaction of individual and collective behavior and based on different self-reinforcing processes. Even if the bounded ability of the actors to process information is an important aspect of the self-reinforcing dynamic of individual learning (Ackermann, 2003:242-243; Schreyögg & Kliesch-Eberl, 2007:919), in collectivities learning also encompasses processes of social interpretation. Interaction and communication between the actors help to align individual beliefs and to create and reproduce shared belief systems (Hedberg, Nystrom, & Starbuck, 1976:48; March, 1991; Pierson, 2000:260). Consequently, in organizational settings complexity acts upon different dynamics. Although complexity presumably creates a fertile ground for path dependence in organizations too (Sydow, Schreyögg, & Koch, 2009:701), its particular effects remain unclear. For example, we may ask if the assumption that specific practices gain momentum more easily (Sydow, Schreyögg, & Koch, 2009:701) is valid. Since a complex environment confronts the organization with a blurry picture, complexity may even contribute to an increased time to lock-in. These ambiguities illustrate that we know little about the interaction between complexity and the particular dynamics at work in organizations.

Another central characteristic of the organizational environment is its stability or predictability (Sharfman & Dean, 1991:684). How often and how profoundly an environment changes has important implications for the unfolding of organizational path dependence. Even if the organization has successfully adapted to its external circumstances, environmental change causes a rationality shift in which a formerly successful pattern flips into a dysfunctional one (Sydow, Schreyögg, & Koch, 2009:695). Persistence in existing organizational patterns like strategies or capabilities despite a change in the environment which calls for new responses is a significant indicator for path dependence. Crouch & Farrell (2004) in their analysis of path dependence in terms of a Polya urn scheme[1] point out a very important aspect concerning an actor's adaptability in a changing environment. The adaptability of the actor depends on the availability of dormant resources, or, in other words, resources that do not reflect the current dominant pattern. These resources create opportunities to counteract impending path dependence. Consequently, if path dependence develops as a crowding out of variety, besides the sheer scope of environmental change, its timing is bound to have a significant influence on the unfolding of path dependence. If the organization is able to perceive and counteract the rationality shift depends on the pull already developed by the self-reinforcing dynamic (Koch, Eisend, & Petermann, 2009:70). Rationality shifts in the path formation phase might thus be perceived and counteracted by the organization. For this reason, we consider timing and scope of environmental change to play an important role in organizational path analysis. Their effects can only be clarified with respect to the particular dynamics at work in the organization.

So far, organizational path dependence theory lacks a clear specification of the dynamics of learning which drive the unfolding of path dependence (Sydow, Schreyögg, & Koch, 2009:705). As a necessary step of our analysis, we therefore refer to the multi-faceted literature on organizational learning and provide a framework which defines the self-reinforcing dynamic of learning effects at the individual and organizational level and which, even more importantly, accounts for their interplay.

[1] The Polya urn scheme represents a classic example of a path-dependent process (Arthur, Ermoliev, & Kaniovski, 1987).

Based on this framework, we move away from isolated individual decision making in complex contexts and inquire into the effects of environmental complexity and turbulence on the specific dynamic of learning effects in organizations.

Research into the effects of different environmental contexts on organizational processes confronts the more conventional research approaches in organization theory, such as case studies or statistical analyses, with insurmountable obstacles. Neither can environments of organizations be modeled and varied at will, nor is the extraction of the influence of complexity and turbulence on a specific isolated dynamic in organizations an easy task. In all likelihood, the results will be confounded by other effects. Moreover, path dependence research has to meet specific requirements. The non-linearity, contingency and in the lock-in state, the long run suboptimality of path-dependent processes are almost impossible to prove in empirical studies (Vergne & Durand, 2010:744-749). Consequently, our research focus points to a simulation approach which allows us to create computational laboratories (Davis, Eisenhardt, & Bingham, 2007:495). A particular simulation approach is of special value for our research focus: models of NK landscapes. NK landscapes are representations of problems of scalable complexity with different locally best solutions of defined value (Ganco & Hoetker, 2008:3-4; Dosi et al., 2011:13). They are therefore not only able to shed light on the non-linearity, contingency and inefficiency criteria of path dependence research but are especially prone to inquiring into path dependence under conditions of complexity and turbulence. We therefore embed the specified learning dynamics in an NK landscape to model the organizational environment as a complex probably shifting problem which the organization has to decipher.

1.2 Dissertation Outline

In essence, a researcher can be described as a problem-solver. Problem solving in a research context is not simply about applying a suitable problem-solving technique, but, is much more about the art *“to solve the problem how to solve the problem”* (Michalewicz & Fogel, 2004:1). Researchers are essentially concerned with framing a problem and thinking creatively. They are confronted with problems that more often than not are complex and cannot be solved easily. Problem solving, therefore, involves, two general steps. The researcher has to create a model of the problem and then has to use that model to arrive at a solution. Consequently, every solution is predominantly a solution to the model of the problem (Michalewicz & Fogel, 2004:16).

The steps involved in problem-solving are reflected in the structure of this dissertation. In our problem statement, we pointed out that in path dependence theory the influence of the environmental context on the unfolding of organizational paths is underexplored. Based on our theoretical approach, we develop a model able to tackle this problem and by experimenting with this model inquire into the effects of the context on path dependent learning processes in organizations.

The dissertation is divided in six major parts. Following the introduction, chapter 2 is concerned with connecting two key strands of theory: organizational path dependence and organizational learning in order to arrive at a theoretical framework for inquiring into the effects of the context on path-dependent processes. We give an introduction to path dependence theory in which we point out the central role of self-reinforcing learning effects for our research focus. Even if learning effects have been identified as a crucial mechanism which drives path dependence, in organizational settings these effects lack a clear specification. Learning adapts an organization to its environment and at the same time harms its adaptability. By building on organizational learning research, we clarify on which levels learning in organizations occurs and discuss its contradicting properties in order to work out the self-reinforcing tendencies of learning processes in organizations. Our theoretical framework encompasses two distinctive learning processes, self-reinforcing individual learning and self-reinforcing learning which involves the organizational level. From their interaction learning in organizations derives its specific properties. Based on our theoretical framework, we describe the role of the environmental context in path-dependent learning and identify complexity and turbulence as relevant characteristics for our inquiry.

In chapter 3, we clarify why computational modeling lends itself for our research focus on the context of path-dependent processes. We outline why simulation research is especially salient to test and build new theory on path dependence and define simulation research as being located in between deductive and inductive approaches in science. We proceed by detailing our simulation approach and discuss the suitability of NK landscapes models for our inquiry. The chapter is completed by introducing the necessary steps involved in doing plausible simulation research.

Chapter 4 takes the necessary next step in conveying the theoretical framework into a model suitable for our chosen methodological approach. In our theoretical framework, we identified two feedback loops, one involving the individual level the other one connecting individual and organizational level. Research in path dependence phenomena requires that a major focus rests on the dynamics of the involved processes. Having specified our methodological approach, in this chapter we discuss how each of the processes in our theoretical framework can be modeled and work out its central dynamic. We introduce the dynamic of mutual learning which is able to reflect how learning is incorporated at the organizational level and the dynamic of individual learning and discuss how far the different models can take us with respect to our research question. We conclude that representing the path-dependent learning mechanism requires an integration of both learning dynamics and finish this chapter by considering the interplay of both dynamics and contemplating their behavior in complex and turbulent environments.

In chapter 5, we put forward our integrated computational model. In contrast to statistical models which do not model mechanisms but correlations, computational models always encompass explicit representations of the processes which are at work in the modeled system (Gilbert & Troitzsch, 2005:18). In this chapter, we define the elements and processes in our model in terms of equations and rules (Harrison et al. 2007:1238). Furthermore, we explain which parameters are used in the model and relate them to our variables as specified in the foregoing chapters.

Computational models are virtual laboratories which can be used to conduct experiments by varying the specified variables of interest. Consequently, chapter 6, is concerned with conducting experiments to inquire into the effects of the environment on the learning behavior of the organization. After setting up our experimental framework in which we prepare our computational model for experimental usage, we first anchor our model in already existing research. For this purpose, we try to replicate conditions and results of mutual learning or NK models thereby showing the effects of isolated mutual or individual learning. The following experiments directly aim at our research question and inquire into the effects of environmental complexity and turbulence. Both environmental characteristics are introduced into the model sequentially. Their implications are discussed for different learning conditions in the organization, always with regard to their effect on the interacting dynamics of mutual and individual learning.

In chapter 7, first we are concerned with the validity of our research and its findings. Subsequently, we discuss the implications of our results for path dependence theory and research in organizations. We proceed by pointing out the limitations of our research and possible future directions and conclude with a brief overall summary.

2 THEORETICAL PRELIMINARIES

In this chapter, we lay the theoretical grounding for our inquiry by drawing on the literature of path dependence and organizational learning.

We begin with a conceptual outline of organizational path dependence. In this part, we emphasize that the environmental context in path dependence analyses so far has not received sufficient attention. We focus on the mechanism of learning as it links an organization to its environment and point out that the characterization of learning effects given in path dependence theory so far needs further clarification.

To clarify the characterization of learning effects, in the proceeding part, we develop a theoretical framework for path-dependent learning. For this purpose, we give a definition of learning which involves the concepts of experience and knowledge and deal with the different levels involved in organizational learning. We proceed by pointing out the ambivalent nature of organizational learning between stability and change. In order to work out a more precise connection between path dependence and organizational learning, we link the self-reinforcing dynamic of learning effects to the dynamic of exploitation crowding out exploration and characterize this dynamic in the interaction of different levels in organizations and in terms of organization-internal variation and selection processes. Based on this discussion, we develop a theoretical framework of path-dependent organizational learning which outlines the self-reinforcing nature of its processes. The knowledge exchange between the different levels in the organization and the competence-enhancing learning conducted at the individual level are identified as the main drivers of path-dependent organizational learning. We conclude this chapter by specifying the organizational environment as moderator of the learning processes and discuss its relevant characteristics.

2.1 Path Dependence and the Environmental Context

This chapter provides a systematic overview of path dependence research. We give a precise account of the properties which characterize path-dependent processes and link these to the different stages of path development. The nature of path-dependent processes is a crucial building block for our study. In subsequent chapters, it will be reflected in our theoretical framework, guide our methodological choice and will be crucial for model building and the interpretation of results.

Following our characterization of path-dependent processes, we discuss prominent analyses of path dependence and illustrate that the role of the environmental context remains surprisingly underdeveloped. Its effects on path dependence are seldom considered. Furthermore, we point out that for an inquiry into the influence of the environmental context on path dependence we need a specification of learning effects in organizational settings.

2.1.1 The Origins of Path Dependence

The notion of path dependence was first used in biology where the development of species was found to be highly dependent on every single step in the evolution process. Path-dependent processes are processes guided by small unforeseeable events and have multiple possible end states. As history matters, such a process can only be interpreted in retrospect. Consequently, not much in evolution would remain unchanged *"if the tape would be played twice"* (Gould, 1989:347).

In economics, path dependence similarly describes processes which are strongly dependent on their history and was found to be closely connected to conditions of increasing returns. In his famous book 'The Wealth of Nations' Adam Smith stated that increasing returns contribute to specialization and growth in the economy. Still, regimes in which the output increases disproportionally to the input by no means became part of the economic mainstream theories. Increasing returns conditions did not gain prominence until the 1980s when process-oriented approaches in economics emerged and questioned the established equilibrium theories. Arthur (1994) outlined the increasing returns perspective as follows:

> *"The increasing returns world in economics is a world where dynamics, not statics, are natural, a world of evolution rather than equilibrium; a world of probability and chance events. Above all, it is a world of process and pattern change."* (Arthur, 1994:xx)

The process-centered view of markets builds on a revolutionary idea. Markets do not naturally favor the best product or technology but can be subject to events that corrupt the workings of the invisible hand (Gartland, 2005:687). Surprisingly, these changes of the market outcome do not result from systemic forces but are the consequence of a sequence of small events which appear to be insignificant.

Paul A. David (1985) and W. Brian Arthur (1989) were the first to deal with the workings of random small events in the adoption process of competing products or technologies. They showed that markets behave differently depending on the type of regime at work. The assumptions of mainstream economic theories of markets as selecting the best product or technology available only hold for settings of decreasing or constant returns. Arthur (1989) even increases the relevance by claiming that most technologies today are subject to increasing returns meaning that the more adopters favor a certain technology the more will follow. This becomes intuitively comprehensible when thinking of current network products like mobile nets, software etc. Increasing returns thus constitute a logic of 'more causes more'. The more people adopt a technology, the more people will follow because an increased number of adopters raises the attractiveness of the technology. A technology that by chance gains a good start in terms of more adopters has an increased probability of outgrowing its competitors. Minor events therefore become magnified by positive feedback and eventually lead to the predominance of an inferior technology. Consequently, in an increasing returns regime markets do not guarantee efficient outcomes.

The most prominent example of such a market process refers to the question asked by Paul A. David (1985) in his seminal paper 'Clio and the economics of QWERTY': *"Why does the topmost row of letters on your personal computer keyboard spell out QWERTYUIOP?"* (David, 1985:332). David leads us back as early as the time of the invention of the typewriter to explain how small events in the beginning of the adoption process helped a keyboard layout to become the universal standard despite the availability of more efficient options. The arrangement of the keys on the QWERTY keyboard resulted from a technical peculiarity of the upstroke machines. Struck in quick succession, typewriter bars could collide and get stuck. The QWERTY key ordering was not designed to increase the efficiency of typing but to prevent typewriter bars from jamming. David identifies several features that in combination made the competition between different typewriters with their respective keyboard layouts subject to increasing returns. Most importantly, using a typewriter effectively requires the keyboard layout to be compatible with the skills of the typist. This compatibility requirement is the basis for a self-reinforcing logic. The attractiveness to acquire typing skills for a specific keyboard layout depended on the types of machines bought by potential employers. On the other hand, the preference of employers for specific typewriters depended mainly on how specific typing skills were distributed in the stock of typists. This mutual dependence enabled small events at the beginning of the adoption process or even expectations about the future distribution of keyboard styles to set in motion a self-reinforcing regime. Each market participant, typist or employer, deciding in favor of QWERTY, increased the possibility that QWERTY would be selected by future decision-makers. Early in the process, the quasi-irreversibility of investment characteristic for the achievement of specialist skills helped to further accelerate the working of the increasing returns dynamic. Whereas touch typing skills could not easily be converted to another keyboard, manufacturers of new non-bar typing machines were not tied to QWERTY but could likewise without difficulty equip their systems with QWERTY keyboards to achieve compatibility with the growing number of suitably skilled typists (David, 1985).

The QWERTY case hinted at several important characteristics of path-dependent processes. Path-dependent outcomes are the result of historical processes in which even minor events can have major consequences due to the magnifying effect of increasing returns. Impossible to predict, path-dependent processes interfere with the logic of the invisible hand and might lead to competitive market failures. In the following chapter, we deal with the properties of path-dependent processes in greater detail using Arthur’s (1989) model of path dependence in technological competition as a starting point.

2.1.2 The Properties of Path-Dependent Processes

The first formalization of path dependence was established by W. Brian Arthur (1989). His formal model adds precision to the historic QWERTY case and gives a general account of a dynamic system that is neither completely deterministic nor totally random but dependent on the unfolding of events (David, 2007). Arthur (1989) creates a model of an adoption process which compares the conditions of decreasing, constant, and as in the case of path-dependent processes, increasing returns. Based on his model, Arthur (1989) specifies the characteristics of path-dependent processes which are still valid today and guide our understanding of organizational path dependence.

In his model, Arthur introduces two kinds of entities, technologies and agents. The technologies, here named A and B, compete for adoption by the agents which are of two types, R and S, as they differ in their preferences for the respective technologies. There is an equal number of agents of each type. When agent i enters the market, he chooses which technology to adopt. His decision depends on his preferences as well as on the number of previous adopters of each technology n_A and n_B and is carried out by conducting a calculation as specified in Table 1.

Returns to Choosing A or B given Previous Adoptions

	Technology A	Technology B
R-agent	$a_R + rn_A$	$b_R + rn_B$
S-agent	$a_S + sn_A$	$b_S + sn_B$

Table 1: Adoptions pay-off for homogeneous agents
(Source: Arthur, 1989:119)

The parameters a and b are specified such that agents of type R have a higher preference for technology A whereas agents of type S have a higher preference for technology B. The parameters s and r define the type and strength of returns, in case of positive values the agents are faced with increasing returns to adoption, in case of negative or zero values they have to deal with decreasing or constant returns to adoption. The agents enter the market and make their decision one after the other, the probability that an agent will be of R- or S-type is one half for each agent. Thus, the only element of chance in this model is the sequence of R- and S-type agents entering the market.

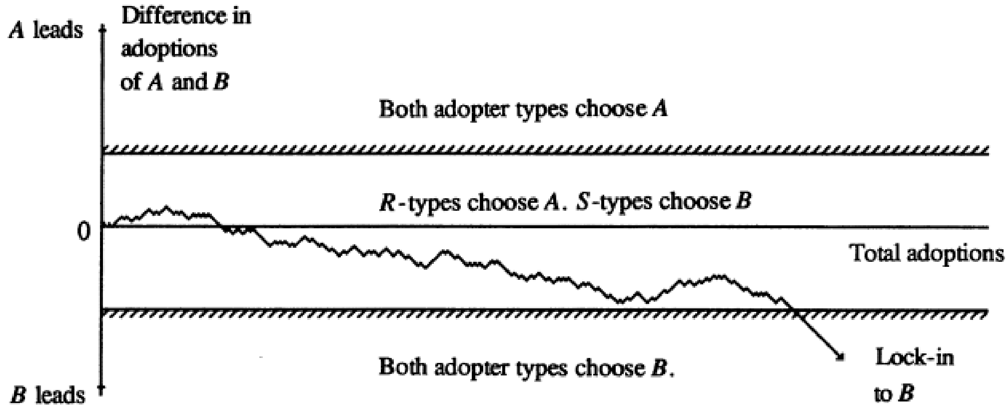

Figure 1: Increasing returns adoption
(Source: Arthur, 1989:120)

As shown in Figure 1, the adoption behavior can be visualized as a process in which each decision by an agent alters the difference in adoption of technology A and B. If the number of adoptions of one technology exceeds the other to a certain amount, even the agent type who originally does not prefer this technology will decide in favor of it. This difference in adoptions, which depends on the strength of the returns to adoption, can be illustrated as a barrier of the process. Depending on the type of regime at work, this barrier either reflects the process as is the case for decreasing returns or it absorbs it as in the case of increasing returns.

Arthur (1989:118-119) characterizes the market process in terms of its ergodicity, predictability, flexibility and efficiency. Whereas the constant or decreasing returns case show all or at least most of these characteristics, Arthur finds the increasing returns case to be nonergodic, unpredictable, inflexible and inefficient. These properties, as a result, became fundamental for the characterization of path-dependent processes and will be discussed in the following with relation to Arthur's (1989) model of technological path dependence.[2]

[2] In chapter 2.1.3, we outline that the different features do not apply to the whole process of path dependence but must be associated with certain phases (Sydow, Schreyögg, & Koch, 2009).

Nonergodicity

Despite David's emphasis on inflexibility and inefficiency in the QWERTY case (1985), in his latter framework on path dependence (2000; 2007) he focuses solely on nonergodicity and excludes the three other properties from a definition of path dependence. Nonergodicity actually proves to be a central characteristic for path dependence and a good starting point as unpredictability, inflexibility and inefficiency partly build on the notion of nonergodicity.

Ergodicity allows us to deal with a variety of deterministic and stochastic processes and decide whether they have the basic properties to be deemed path-dependent. In brief, an ergodic system is able to shake free from the historical influence of past states it went through (David, 2007:97) and can thus be considered path-independent. Take, for example, the model of two competing technologies in a regime of constant returns. Here every agent who enters the market will choose the technology he prefers without having to consider the decisions of previous adopters.[3] The adoption process will therefore reflect the random order of decision-maker types. Following the law of large numbers, with an increasing number of adoption decisions, the market shares of the two technologies will eventually each approach fifty per cent for each technology. Independent of the historical sequence of events, in our case independent of the sequence the different types of adopters which entered the market, the same market outcome will be achieved with probability one (Arthur, 1989:122). More generally speaking, ergodic processes include processes which converge to form a unique globally stable equilibrium independent of the way the equilibrium was reached, as it is usually the case in neoclassical models of the market.

In case of stochastic systems without absorbing states, ergodicity means that in the limit a unique positive probability can be given to every feasible position the system can adopt within space independent of the initial conditions. As such, these kinds of systems will take on all of these positions sooner or later. Consequently, ergodic systems are characterized by their ability to move between any of the possible states. They eventually rid themselves of imprints from the past. Common examples are

[3] The second part of the equation in table 1 then amounts to 0.

Markov chains[4] in economic distribution models of for example income, wealth, or firm size (David, 2000; 2007; Horst, 2008). Another famous example of a Markov chain is the drunkard's walk. Every step of the drunkard along a numbered line depends solely on his current position as he chooses at random to take one step ahead or backwards ($+1$ or -1 along the line). Independent of where on the line the drunkard currently stands, sooner or later he is able to reach any other position on this line. His transition probability is an invariant function of his current state.

In contrast, in nonergodic processes the transition probability is influenced by the history of the process, giving the process an irreversible quality. As the system proceeds through time, the states it passes through amount to a stronger and stronger influence which finally selects between the different potential outcomes of the system. Reaching alternative outcomes from states further down the path of history becomes virtually impossible, not merely the current position but the whole history of the process influences the likelihood of future states.

Nonergodicity is a central property of path-dependent processes. In sum, a nonergodic process evolves as a consequence of the process' own history. The sequence of events determines for which of the multiple possible outcomes the process will settle (Sydow, Schreyögg & Koch, 2009). Consider the case of increasing returns in Arthur's model. Agents that enter the market and make their decision for technology A or B change the returns of the respective technology which the following agents will have to take into account. As soon as there are enough adopters of, for example, technology A the returns this technology generates will outcompete the returns of technology B even for the S-agents who actually have a higher preference for B. Generally speaking, if the number of adoptions surmounts an absorbing barrier the system will lock-in on one technology as both agents, independent of their preferences, from then on choose the same technology (Arthur, 1989). The case of increasing returns thus is a nonergodic process, for which of the two possible outcomes, complete dominance of technology A or B, the process will settle, is determined by the history of events at the beginning of

[4] Markov chains exhibit no memory; the state of the system at time $t+1$ depends merely on the position at time t. For an example see the famous Markov chain, the drunkard's walk, http://en.wikipedia.org/w/index.php?title=Markov_chain&oldid=473334332.

Markov chains can become path dependent if they possess two or more absorbing subsets.

the process before crossing one of the absorbing thresholds. In the constant returns case, the central limit theorem holds. Given the number of adoption decisions is high enough, eventually both technologies will divide up the market in equal shares. In the increasing returns model, however, the small movements of the system will not be averaged away even in the case of a large number of adoption decisions, they determine whether the system will lock-in on technology A or B (David, 2007).

Nonpredictability

There seems to be some disagreement about the notion of nonpredictability in the first path dependence models which might also have contributed to the debate about and critique of path dependence.[5]

David's (1998) definition of an unpredictable process differs from the interpretation given by Arthur (1989). In David's (1998) nonergodic system of opinion distribution, the initial opinion configurations of the agents can be used to predict the macro-state system configuration if not with certainty then at least probabilistically. In Arthur's (1989) approach, predictability was defined in relation to the outcome of a single run of his market model. If the events, here the sequence of adoption decisions of the agents, lose their influence on system behavior in the long run than the model is said to be predictable; in the constant returns case the forecast that the market will settle for a 50:50 solution of both technologies is correct with probability 1. For the increasing returns case, one of the technologies will capture the whole market. An observer making a guess for one of the technologies will be wrong with probability one-half, the market outcome cannot be predicted for sure but only be probabilistically assessed.

For David (1998:148-149), predictability of a process is given if a probabilistic assessment concerning its multiple possible outcomes can be made, whereas Arthur (1989:122) calls a process predictable if the outcome can be forecasted with

[5] Liebowitz & Margolis (1995) define three different degrees of path dependence and consider the first two to be irrelevant as their market outcomes could also be explained by mainstream economic approaches. They argue that third degree path dependence is the only type which conflicts with the neoclassical model and simply dismiss this type by referring to the allocating processes of markets based on the profit seeking behavior of the market participants (Liebowitz & Margolis, 1995:207-209). In his answer, David (2000; 2007) criticizes Liebowitz & Margolis (1995) for neglecting to deal with the different characteristics of path-dependent processes and instead being predominantly obsessed with their inefficiency. See also footnote 9.

probability 1 which means that the process has only one possible result. In essence, when defining predictability, the two researchers differ in the focus concerning the processing of the model. A probabilistic approach to predictability, as in David's case, rests on the assumption that the model is repeated very often, so that a statement about the frequency of the possible results over all iterations can be made. Arthur (1989), in contrast, for his definition of unpredictability focuses solely on one model cycle for which the result cannot be predicted for sure. Nonergodic processes, as dealt with above, seem to automatically involve unpredictability in Arthur's sense as they have several possible outcomes. For David path-dependent processes are above all nonergodic processes which can have a probabilistic predictable or unpredictable nature. Thus, we are thrown back on the nonergodicity characteristic of path-dependent processes.

Nevertheless, this discussion shows us an important aspect about the relation of path dependence models and the real world. Unpredictability is the only characteristic in Arthur's (1989) model that is defined from the point of view of an observer embedded in the system. The properties of a path-dependent system might differ whether dealing with it from the perspective of the model builder or from the point of view of an observer who has limited resolving power (Arthur, 1989:120). Much like a person in the real world, the observer might be able to determine that the process has several possible outcomes and predict that one technology will take the lead. But unlike the model builder, who uses the model to get a clue with which probability the system will lock-in on A or B, the observer evaluates only a single system cycle whose result will be unpredictable for him. As such, the property of nonpredictability in Arthur's (1989) model is closely connected to observing path dependence while being embedded in the system. Nonpredictability, thus, reminds us that path-dependent phenomena are complex social processes which for the people absorbed in them are difficult to understand. Still, as all social processes are unpredictable and involve multiple possible outcomes (Petermann, 2010:121), non-ergodicity specifies them to build on an unfolding sequence of small events which are not cancelled out by history but feed back in future choices (Pierson, 2000:253).

Inflexibility

In Arthur's (1989) model of adoption decisions, a process is claimed to be flexible if at any time in the process a tax adjustment or subsidy could convince adopters to decide against their preferred technology. Whereas nonergodicity emphasizes the importance of small events in the process, inflexibility refers to how they relate to each other. Processes become inflexible because they exhibit a self-reinforcing logic. The occurrence of one event increases the probability for a similar event to happen.

In the market model with increasing returns, every adopter of a technology increases its attractiveness for future adopters. The adoption process is a random walk before it crosses one of the absorbing barriers where the returns to adoption of one technology make it strong enough to render the different preferences of the agents meaningless. From then on, each of the two agent types would decide for the same technology: The process becomes inflexible. Obviously, inflexibility refers to determinacy of outcome. After crossing the absorbing barrier the outcome of the process is certain. Trying to bring flexibility or alternate possibilities, as in this case the other technology, back in, would require shifting the absorbing barrier. Since the increasing returns to adoption lead to a self-reinforcing spiral of ever increasing attractiveness of the leading technology, the tax adjustment needed to shift the absorbing barrier is also increasing without limits (Arthur, 1989:122). Contrast this with the case for decreasing returns. If the difference in adoptions in favor of one technology becomes high enough, the adoption process will favor the other technology. The barriers in the adoption process become reflecting, and the adoption process moves only within the limits of the barriers. Since we do not experience a self-reinforcing logic, the process does not reach an inflexible state.

Whereas nonergodicity characterizes processes as having multiple outcomes which develop as a consequence of small events inflexibility adds a new aspect. A path-dependent process finally leads to a point of no return which in Arthur's (1989) model is represented by the absorbing barriers. From here on, the system is locked to one specific result. Inflexibility is therefore, a characteristic of the final phase of a path-dependent process (Sydow, Schreyögg, & Koch, 2009:694-695).[6] Consequently inflexibility also seems to be suitable to differentiate path-dependent processes from

6 For an explanation of the different phases of a path-dependent process see chapter 2.1.3.

certain types of nonergodic processes as mentioned in David (2000, 2007; see also Sydow, Schreyögg, & Koch, 2009:695). Branching processes, as for example processes of speciation in biological evolution, are nonergodic processes including irreversibilities. They involve 'forks in the road', going down one branch of the fork leads to a region from which the alternative branches are unattainable. These processes have an irreversible quality as a return to the branching point, once passed, is impossible, but they do not involve an inflexible outcome. A process of speciation is an ongoing process; it does not entail inflexible end states. Inflexibility as a characteristic of a path-dependent outcome, consequently, contributes to sharpening the path dependence perspective and in the context of organizations is well-suited to reveal the danger which arises from path-dependent phenomena.[7]

Inefficiency

In the QWERTY case study (David, 1985), inefficiency plays a central role: It is the point of departure for David's analysis. He set out to explain why a market stays with a suboptimal solution (Sydow, Schreyögg, & Koch, 2009:695). Observed inefficiencies until today remain a valid starting point for the analysis of paths.

In Arthur's (1989:119,122) definition of inefficiency, the notion of regret is central. A system state is inefficient if some actors experience regret because an equal development of the outcompeted technology would have made them better off. This is the case in the regime with increasing returns. Every agent of the type which favors the non-winning technology, experiences regret. If his preferred technology had an equal amount of supporters as the leading one he would be better off. The assessment of inefficiency, thus, often involves identifying alternative routes of history and judging their future potential in relation to the realized alternative. Whereas in economics inefficiency can be defined with relation to the pareto-optimal solution, in the context of organizations inefficiency must be assessed differently.

The new process perspective of QWERTYnomics would have lost much of its explosiveness, had it concentrated solely on non-ergodic processes, as David proposed in his latter framework on path dependence (2000; 2007). It was first of all the

[7] For a discussion of inflexibility as a result of organizational learning processes see chapter 2.2.4.

property of inefficiency that challenged the economic main stream. The claim that a system can remain in an inefficient state criticizes the static framework of welfare analysis. It asserts that economic systems evolve as a result of historic processes and as such can lose their potential to rapidly eliminate inherent inefficiencies. The rapid removal of inefficiencies by profit-motivated actors is what justifies the ahistorical standpoint of mainstream economists (David, 2000:106). Based on this assumption, every system will converge to an efficient equilibrium which can be analyzed in a static way; inefficiencies due to changed circumstances are exploited quickly by the system which then again finds itself in the optimum state. In mainstream economics, inefficiencies as opportunities for profit-seeking actors are the motor behind equilibrating forces of the market. Even if David argues against an obsession with inefficiency (David, 2000:7),[8] inflexibility and inefficiency must be considered necessary criteria for path dependence.[9] Two different aspects of the relation between inflexibility and inefficiency stand out here: Consider the path-dependent end state in a stable environment as, for example, in most models of path dependence. In the case of an efficient outcome, inflexibility loses its perplexing property as the actors in the system have no incentive to change. Inflexibility has therefore to be combined with inefficiency to conceive of path dependence as a puzzling persistence (Sydow, Schreyögg, & Koch, 2009:695). In the case of a changing environment, path dependence at least is concerned with potential inefficiency. In a changing environment, even an efficient system state which is inflexible involves the strong likelihood, if not certainty, of becoming dysfunctional in the future.

8 David (2007:105) also argues that sometimes it may be difficult to decide if a system state is actually inefficient.

9 Inefficiency also stood at the center of great debate regarding the plausibility of the path dependence concept because the possibility of an enduring inefficient market state casted serious doubt on the validity of the neoclassical paradigm. In their forceful critique, Liebowitz & Margolis (1995) differentiate between three degrees of path dependence in order to show that the concept does not pose a threat to neoclassical processes of allocation, as in the case of path dependence of degree one or two, or if it contradicts the established theory, as is the case with third degree path dependence, it is most unlikely to happen. Furthermore, they try to demonstrate that prominent examples of path dependence are not cases of third degree path dependence. In their differentiation of the three degrees of path dependence, Liebowitz & Margolis (1995) focus on the remediability of an inefficient market outcome. In a Panglossian kind of way, they determine a result to be the best one achievable by imperfectly informed but still rational actors if only its remediation costs are high enough (Castaldi & Dosi, 2004:19-20). The effort of Liebowitz and Margolis (1995) thus follows a long since employed strategy of neoclassical economists; they try to reduce the relevance of the new emerging theory so that it can be incorporated in their existing framework.

At the end of this chapter, we have arrived at the following precise account for path dependence. Whereas nonergodicity relates to the way the path-dependent process unfolds in time, inflexibility and inefficiency specify the outcome of such a process. A path-dependent process evolves as a consequence of its own history; the sequencing of events determines which of the multiple possible outcomes will be chosen. Due to its history, the system is finally entrapped in a suboptimal end state. Path-dependent processes therefore can be defined as nonergodic processes with inflexible and inefficient outcomes.

2.1.3 The Process Model of Organizational Path Dependence

As hinted at in the preceding chapter, path-dependent processes do not exhibit all described properties from their outset to the final lock-in. Rather, as Sydow, Schreyögg, & Koch (2009:691) claim that, for a better understanding of the process' dynamic, these properties must be linked to the different stages of unfolding paths.

Following the logic of Sydow, Schreyögg, Koch, (2009), a path-dependent process consists of three stages which are each covered by specific properties. A path building process starts with the preformation phase, a historically imprinted contingency, in which small events might set in motion self-reinforcing mechanisms. This marks the beginning of the path formation phase in which the self-reinforcing logic increasingly narrows the organizational scope of action. In the final lock-in phase, the prevailing action pattern becomes fixed, leaving the organization inflexible and bound to an inefficient path.

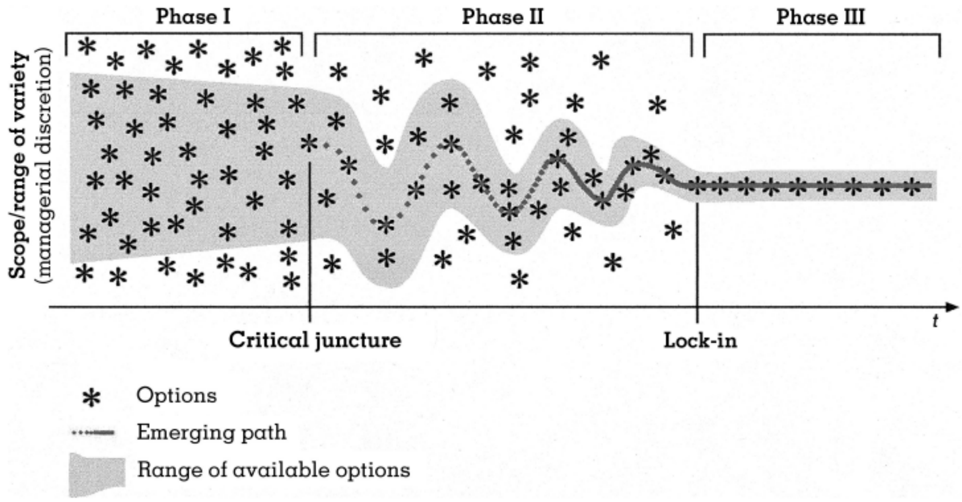

Figure 2: The unfolding of an organizational path
(Source: Sydow, Schreyögg, & Koch, 2009:692)

Preformation Phase

The first stage of a path unfolding process is characterized by an open situation in which choice is mostly unrestricted. In Arthur's (1989) increasing returns model the process, before crossing one of the absorbing barriers, was equated with a random walk and is essentially unpredictable for the embedded observer. Each event in the beginning of the process can be considered to display two properties, it is random and small. The type of the next agent entering the market is chosen by chance and the influence of his decision on the market process up to a certain threshold, when crossing the absorbing barrier, is insignificant.

In a theory of organizations, we have to take a closer look at the two characterizing features of events in path dependence. They are both linked to our understanding of contingency which is the central property of the first stage of a path-dependent process. In the path dependence literature, contingent events have sometimes been equated with mere chance events (Vergne & Durand, 2010:741-742) whereas others argue that contingency cannot be assessed independent of theory (Mahoney, 2000:507-508). In this line of thought, the property of contingency does not imply that an event is truly random but that it falls outside the explanation of prevailing scientific theories. This can involve small events that are too specific for a theoretical explanation such as particular individual choices or large events, such as natural disasters (Mahoney, 2000:513; Deeg 2001:9).

In systems theory, contingency builds on the original notion of Aristotle and refers to an event which is not impossible but not necessary (Luhmann, 1984: 152). A contingent event is therefore neither completely random nor without antecedent causes, but cannot be determined by initial conditions either. The unpredictability which Arthur's (1989) embedded observer experiences is therefore a result of the contingent character of events. A nonergodic process necessarily must begin with contingent events as these are a precondition for multiple possible outcomes.[10] That the events in the beginning state of an organizational path cannot be considered completely random is also due to the fact that the initial situation is open but not entirely unrestricted.[11] It is imprinted by the past reflecting the inherited rules and culture of the organization (Sydow, Schreyögg, & Koch, 2009:692). The shadow in the preformation phase in figure 3 indicates these historical imprints.

In social systems like organizations, initial events might also reflect intentions of the actors as displayed by certain strategic moves. This would further limit the randomness of initial events and also question their smallness (Sydow, Schreyögg, & Koch, 2009: 692). Mahoney (2000), Pierson (2000), and Deeg (2001) agree that events in path building processes do not necessarily have to be small and random but can be bigger in terms of their significance and also reflect the goal-directed behavior of actors.[12] [13] Even if the initial events in early organizational path developments reflect the properties of social systems which make them less innocent and small, they

[10] Interestingly, contingency and its result unpredictability often seem to be closely connected to the way actors perceive the world. The theory-oriented definition of Mahoney (2000:507-508) even concludes that the perception of contingency depends on the researcher's type and probably amount of knowledge.

[11] Ebbinghaus (2005:16) distinguishes between two types of path dependence, diffusion and developmental pathways, by referring to different types of events. Mere chance events which characterize diffusion models similar to Arthur's (1989) approach and events based on the more or less conscious decisions of actors which finally lead to the emergence of an institutional path. In learning, events must be considered to be of the second type.

[12] For a different point of view see Vergne & Durand (2010:742). Their definition of contingency is based upon randomness.

[13] Whereas Mahoney (2000:507) and Pierson (2000:251) both define contingent events as a necessary condition for path dependence, for Deeg (2001:35) also non-contingent events can stand at the beginning of path-dependent processes. He defines non-contingent events as events *"that functioned as intended by their creators"*.

are not causal determinants of the process either.[14] The outcome of the path process is generated by a sequence of events which cannot be known in advance and in the beginning of a path process is essentially contingent, in the sense that the outcome will be just a possible but not a necessary consequence of the past (Lehmann-Waffenschmidt, 2010:482).

Formation Phase

The nature of the process changes when entering the formation phase which is characterized by a dynamic of increasing returns. The tapering walk of the preformation phase changes dramatically as one event finally pushes a cumulative variable over a certain threshold which unleashes a self-reinforcing dynamic (Deeg, 2001:20). This critical juncture separates the first from the second phase of a path-building process. From then on, the organizational scope of action increasingly narrows. It is the formation phase in which contingency slowly gets lost, as is indicated by the narrowing shadow in Figure 2, and is finally replaced by a deterministic action pattern (Sydow, Schreyögg, & Koch, 2009:694). The self-reinforcing dynamic is not deterministic from the very beginning but, initially, still leaves room for alternative courses of action or at least different variations of the emerging path. But in the end, it is the self-reinforcing dynamic which makes the outcome of a path-dependent process not only an inert end state but gives rise to an ever increasing inflexibility which, without understanding the logic of the self-reinforcing mechanisms at work, cannot be broken. These mechanisms in organizational path dependence are based upon different features than the mechanisms in economics which mainly involve ever increasing utility of a product or technology due to the interlocking of application scope and the number of users. In organizational path dependence, the self-reinforcing mechanisms reflect the specialties of organizational life (Sydow, Schreyögg, & Koch, 2009:694).[15]

[14] An interesting distinction is introduced by Lehmann-Waffenschmidt (2006:27). He differentiates between situational or decision-based contingency and system-generated or structure-based contingency. The events of the different types of contingency originate at different levels. In decision-based contingency actors can generate events, whereas in structure-based contingency events originate at system level.

[15] For an explanation of self-reinforcing learning effects see chapter 2.1.5.

In Arthur's (1989) model, a path building process starts out as an entirely random walk and is completely determined after it crosses the barriers. In the emergence of an organizational path, history imprints this process from the very beginning; even after the critical juncture, while being constrained by the onsetting regime of increasing returns, the organization's action pattern does not enter complete determinacy. In organizational life, decisions have a greater scope than simply opting for technology A or B. Organizational behavior offers a more complex picture, it exhibits a greater variety in interactions of actors and is shaped by experience and learning on organizational and individual level.

Lock-in Phase

The organization leaves the path formation and enters the lock-in phase when the preferred action pattern reaches a high degree of inflexibility. The rigidity of a lock-in implies more than a stable situation with high cost of reversal. The self-reinforcing mechanisms in path dependence give rise to an ever increasing stability of the organizational core pattern. Still, organizations unlike markets are not completely determined in this situation. Rather, the predominant social influence provides guidelines for organizational action but leaves some room for interpretation by organizational actors. Thus, while observing an organizational path, we might find some variation in the way it is practiced (Sydow, Schreyögg, & Koch, 2009:695). Figure 2, therefore, shows the organizational path not as a line but as a corridor which restrains organizational action.

Even if there might be some variation in practicing the path, this must not be mistaken with real scope of action. Vergne & Durand (2010:743) characterize a lock-in as *"a state of equilibrium with a very low potential for endogenous change"*. The notion of equilibrium, however, might cause some confusion in this context. Equilibrium in the foregoing definition must not be mistaken with the neoclassical notion of a unique optimal allocation of goods on a market. It refers to one of several possible stable end states of the system which are contingently selected, based on sequences of events which give rise to self-reinforcement. In a lock-in, organizational behavior is rigid; self-reinforcing loops ultimately drive the organization in a situation which is characterized by inflexible managerial beliefs and possibly also resources. The organization loses its internal potential for change and is left unable to react to its environment.[16]

The most precarious characteristic of the organizational lock-in, its potential inefficiency, is closely connected to the inflexibility of this final phase of a path-building process. Even if the self-reinforcing process brings about a situation which is well suited for the current organizational environment, it could only be characterized as an efficient result under conditions of environmental stability. Organizations may even be drawn to these initially efficient results as these go along with the highest reinforcement earnings. But due to the self-reinforcing processes at work, these earnings bring about an unintended inability to change (Sydow, Schreyögg, & Koch, 2009:695; Schreyögg & Sydow, 2011:325). Good examples are capability-based practices. Once chosen for their success in a specific situation, they become embedded in the organization due to self-reinforcing learning effects[17] and bind the organization to the past (Leonard-Barton, 1992:123; Schreyögg & Kliesch-Eberl, 2007:916-917). If we consider environmental turbulence, an efficient but rigid situation therefore always comprises the potential for inefficiency.

2.1.4 The Missing Environmental Context in Analyses of Path Dependence

From its place of origin, explaining market processes in economics, path dependence has developed into an important lens for the interpretation of social processes on various levels and in different disciplines (Vergne & Durand, 2010:737).[18] In economic sociology, and political economics, path dependence is used to explain institutional persistence on the macro level (North, 1990; Mahoney, 2000;

[16] Considering this low potential for endogenous change, Sydow, Schreyögg, & Koch (2005:21-26; 2003:273-281) suggest that breaking an organizational path requires intervention from outside the system. They refer to discursive, behavioral, and systemic approaches to alter the often unconscious routines resulting from path formation. Schreyögg & Kliesch-Eberl (2007:928-930) propose to install a separate process to monitor organizational capabilities. Vergne & Durand (2010:737) claim that lock-in can only be diagnosed in the absence of exogenous shock.

[17] See chapter 2.1.5.

[18] For an overview of path dependence approaches in different disciplines and on different levels of analysis see Gartland (2005: 690). Still, his definition of path dependence remains somewhat unclear involving mostly the suboptimal outcome.

Pierson, 2000; Djelic & Quack, 2007). At the core of this research stands the stabilization and reproduction of societal rules and cultural patterns. On the meso level, economists and organizational scholars consider technological trajectories and organizational governance to be the result of path-dependent processes (Arthur, 1990; Cowan, 1990; Williamson, 1999). In organization science, however, most of the analyses of path dependence deal with rigidifying tendencies on the micro level of capabilities and strategies (Leonard-Barton, 1992; Egidi & Narduzzo, 1997; Teece, Pisano, & Shuen, 1997; Helfat & Raubitschek, 2000; Eisenhardt & Martin, 2000; Helfat & Liebermann, 2002; Schreyögg & Kliesch-Eberl, 2007).

Even if path dependence started out as a rather well-defined concept in the realm of economics, while making its way through the different disciplines, it was linked with various properties which obscured its meaning and often made it a simple surrogate for rigidifying tendencies and organizational inertia. A broader conception of path dependence as merely a process of evolution in which the events at an early point in time affect the following process' trajectory (Nooteboom, 1997:57) lacks 'theoretical bite' (Mahoney, 2000:205; Djelic & Quack, 2007:163) as every process is imprinted by the past. Sydow, Schreyögg, & Koch (2009:690) conclude that equating path dependence with a mere history matters argument turns it into a truism.[19] Let us recall that in Arthur's (1989) framework only the increasing returns process exhibits all four properties of path dependence. The self-reinforcing logic thus belongs to the core of path dependence.[20] In a reflection of the role of the environmental context in path-dependent analyses, we therefore have to bear in mind that path dependence has a long history of rather undefined and metaphorical usages which must be separated from approaches which build on the original concept of path dependence as forwarded by

[19] David (1997:25) gives an account of three different degrees of historicity in economic dynamics. Whereas weak and medium historicity indicate that every process has some sort of direction which leads us from the present to the future and that the transformation from one state to another cannot take place instantaneously but involves a sequence of steps, strong historicity refers to dynamic systems which meet the conditions of path dependence. While equating path dependence with weak historicity renders it dispensable and turns it into just another word for rigidity, strong or, in other words, precise conceptions enable it to explain phenomena which other theories cannot (Vergne & Durand, 2010:741).

[20] Please note that Page (2006:88) differentiates between increasing returns, self-reinforcing, and positive feedback: *"Increasing returns means that the more a choice is made or an action is taken, the greater its benefits. Self-reinforcement means that making a choice or taking an action puts in place a set of forces or complementary institutions that encourage that choice to be sustained. With positive feedbacks, an action or choice creates positive externalities when that same choice is made by other people."* Following other studies of path dependence (Mahoney, 2000; Sydow, Schreyögg & Koch, 2009), here these expressions are treated as synonyms.

David (1985) and Arthur (1989). We analyze, in the following, to which extent approaches which considered path dependence to be a product of self-reinforcing processes dealt with contextual influences.[21]

With his historical description of the adoption process of the QWERTY keyboard, David (1985) gave an exemplary account of a path-dependent process. Case studies are a very prominent research design for analyses of path dependence. Even if case studies might provide some indication as to how the embedding environment influenced the analyzed case, in general, case studies are not able to compare the development of the case for different contextual conditions. We therefore conclude with Vergne & Durand (2010:750) and Zott (2003:109) that the drawback of case studies as relying on the analysis of merely one historical path, makes them unsuitable as the basis of an inquiry into the effects of different contextual conditions on path dependence and, similarly important for our research, does not enable us to generalize about the underlying mechanisms of self-reinforcement.

Arthur (1989) provided a general model of an adoption process for which the type of returns generated in the process can be varied. His results offer conclusive and generalizable evidence as to how increasing returns affect the process dynamic. But even if Arthur (1989) provides us with general criteria for a path-dependent process, his model does not allow us to conclude how the self-reinforcing process of path development would turn out under different environmental conditions. Along with the return functions of the technologies which must be considered as being determined by the context or the technology itself, the environment is hidden in the basic assumptions of this model, headmost the assumption of perfect information. The agents at every point in time are perfectly informed about the differences between adoption numbers of the competing technologies A and B. Other factors which are central to models of adoption, as the structure of the network connecting the agents, or ratio and distribution of adopter types lies outside of the scope of Arthur's (1989) model.

North (1990) in his analysis of the path of institutional development which closely follows David's (1985) and Arthur's (1989) concept of path dependence already

[21] The self-reinforcing logic also clearly tells organizational path dependence apart from the seemingly related concepts of imprinting, sunk costs, escalating commitment, and structural inertia (Sydow, Schreyögg, & Koch, 2009:696-698).

criticizes Arthur (1989) for not involving the context of the technologies, in this case organizations, in his model:

> *"Arthur deals with competitive markets in which agents respond to maximizing opportunities; he is analyzing competing technologies, both of which are subject to increasing returns. In fact (…), the competition is only indirectly between technologies. Directly it is between organizations embodying the competing technologies. The distinction is important because it may reflect differing organizational abilities (…) as much as specific aspects of the competing technologies. Indeed, ultimately Arthur is dealing with decision making in organizations"* North (1990:94-95)

For this reason, North (1990:96) considers two forces to shape the development of institutional paths: self-reinforcement and the embedding context characterized as imperfect markets exhibiting high costs of transacting. Imperfect markets in North's approach are a necessary precondition for path dependence (Koch, Eisend, & Petermann, 2009:68). Without transaction costs, North (1990:96) claims, increasing returns would not lead to a multitude of possible paths nor would the outcome be an inefficient one. Inefficiency can only prevail if the actors with their mental constructs, ideas and theories have difficulty in coping with the complex environment.

For North (1990) contextual complexity is necessary for the development of a path-dependent result. Pierson's arguments (2000) go in a similar direction. For him, more complex environments have a higher inclination to show path dependence. Pierson (2000) claims that the murkiness of the political environment makes path dependence much more prominent in political systems. In agreement with North (1990), Pierson (2000) considers self-reinforcing dynamics to develop a stronger pull in contexts of complex social interdependence and characterizes complexity and ambiguity as preconditions for path dependence.

However, there seems to be some disagreement in path dependence studies if specific contextual conditions must be considered necessary for path dependence to come about. In contrast to North (1990) and Pierson (2000), Sydow, Schreyögg, & Koch (2009:701) argue that characteristics of the institutional environment are important aspects which hinder or promote path dependence, but cannot be conceived as necessary conditions in their own right. In chapter 2.2, we give a detailed account of the learning dynamics at work in organizations. Apparently in learning, complexity and bounded rationality must be considered in combination (Koch, Eisend, &

Petermann, 2009:71). Leaving problem complexity out of the picture, or in other words confronting learners with too simple a problem, makes bounded rationality dispensable. Clearly, the limitations of learning and the learning environment are closely connected (Gigerenzer & Todd, 1999).

Even if Pierson makes a good point by emphasizing the role of the environmental context for path dependence studies, he fails to deal with the specific influence of precise contextual characteristics (Koch, Eisend, & Petermann 2009:68). This shortcoming also seems to invoke some vagueness when differentiating between self-reinforcing mechanisms and contextual features. Pierson (2000:259), for example, seems to consider power structures as self-reinforcing in their own right. Obviously, it is not the aim of his study to focus on a specific dynamic of self-reinforcement and its relation to its environment but to give a more general account involving the whole breadth of path-dependent dynamics and environmental features.

Mahoney (2000) claims that, in addition to self-reinforcing mechanisms, reactive sequences of events can lead to path-dependent outcomes.[22] Reactive sequences simply are chains of successive, causally connected events (Mahoney, 2000:526). Even if Mahoney (2000:533-535) shows how environmental sequences can be linked to or result in cultural or industrial sequences, reactive sequences cannot be considered as processes of path dependence. Reactive sequences as such are cause and effects chains in which each event is connected to the foregoing. Compared with self-reinforcing processes there is no overall connecting logic between the events in a reactive sequence, or in other words, the events do not accumulate (Sydow, Schreyögg, & Koch, 2009:698).

The experiment of Koch, Eisend, & Petermann (2009) follows the clear-cut definition of path dependence as resulting from positive feedback processes and inquires into contextual effects on individual decision-making. In their experiment, the authors indicate that feedback in decision making not only confirms the already taken decision but also impacts on future decisions. Unlike the single case study approaches which are common in path dependence studies, the controlled research design allowed for deliberately varying the conditions in which the individual decision-making took

[22] For Arrow (2003), path dependence is driven by quasi-irreversibility of investment. Not only settings with increasing returns but with constant returns can exhibit path-dependent behavior.

place. We can draw from their research that complexity of the decision-making context significantly affects individual path dependence. As Vergne & Durand (2010:750-751) confirm, laboratory experiments are especially useful when testing path dependence at the individual level. But for an inquiry into organizational path dependence laboratory experiments soon reach their limits. Organizations are systems of interconnected individuals which are difficult to replicate in laboratory settings.[23] Even if Koch, Eisend, & Petermann's (2009) study points to the relevance of environmental complexity for the unfolding of path dependence, it is focused on the atomistic setting of individual decision-making and does not deal with its organizational embedding.

The most elaborate model concerning the role of the context for path-dependent processes was developed by Crouch & Farrell (2004). Building on the famous Polya urn model (Arthur, Ermoliev, & Kaniovski, 1987),[24] Crouch & Farrell (2004) discuss how actors respond to their environments. Actors are modeled as Bayesian decision makers and seek to align their behavior with environmental demands. Instead of merely featuring one urn as in the classical Polya urn example (Arthur, 1985), the environmental state and the actor's repertoires are represented by separate urns containing balls of two different colors. The model therefore allows inquiry into the effects of environmental change as a switch of color from the environment urn. Crouch & Farrell (2004:24) also extend their model of an isolated decision maker to represent a collective agent whose components can learn from each other. In this case, the actor is able to choose between two different urns and thus incorporate experience from different action spaces. Crouch & Farrell's (2004:17) model reveals important points concerning the influence of environmental change on path dependence. Dormant resources, or in this case balls of the non-dominant color, are crucial for path-dependent systems confronted with environmental change. They provide alternative repertoires and therefore a means for reacting to path dependence. The abundance of dormant resources as a variety of different repertoires to be accessed by

[23] See on this chapter 3 dealing with our methodological approach.

[24] The Polya urn process (Arthur, Ermoliev, & Kaniovski, 1987) depicts the general increasing returns logic. Consider an urn which contains two balls, a white one and a red one. If every time, an agent draws a ball, the ball is replaced and an additional ball of the same color is added, the eventual distribution of colors in the urn after a large number of draws will eventually be dominated by one color. The dominating color is a result of the sequence in which the colors are drawn.

the actor also reveals that it is crucial when the environmental change occurs.[25] The adaptability of the actor is closely connected to the color distribution in his urn. The approach of the model on decision-making or, as Crouch & Farrell (2004) claim, learning in collectivities which is represented by the central actor choosing between two different urns neglects important characteristics which are central to interaction in organizational settings. Learning in organizations always involves different levels (Argote & Miron-Spektor, 2011:4). It must not be represented as a central actor selecting between different possibly path-dependent options. We must consider path dependence in organizations to evolve on a collective level for which individual beliefs are combined and incorporated. In the subsequent chapter, we deal with the mechanism which connects organization and environment and consider how it is specified in path dependence theory.

2.1.5 The Self-Reinforcing Learning Mechanism in Organizational Path Dependence

Path dependence theory differentiates between four mechanisms which, alone or in combination, can cause organizational path dependence. In the first economic approaches to path dependence, several self-reinforcing mechanisms were determined to drive the dynamics at the market level (David, 1985; Arthur, 1994). In organizations, however, the path-driving mechanisms rely on different causal structures which reflect the peculiarities of organizational life.

Path dependence theory strongly underlines the importance of social mechanisms of a specific type for the unfolding of the organizational rigidity. This mechanism focus reveals that path dependence theory is a process theory which concentrates more on describing the way input and output variables are connected than on their statistical correlation.[26] Mechanisms open up the black box of statistical analysis and describe how a relationship between an input and output variable is brought about (Hedström & Swedberg, 1996:288). Bechtel & Abrahamson (2005) come up with a useful definition:

25 We deal with the significance of internal variety for our model extensively in chapters 4.1.1 and 4.1.2.

26 In chapter 3.1, we explain the consequences of the process focus of path dependence theory for the choice of our research method.

> *"A mechanism is a structure performing a function in virtue of its component parts, component operations, and their organization. The orchestrated functioning of the mechanism is responsible for one or more phenomena."* (Bechtel & Abrahamson, 2005:243)

Pajunen (2008) clarifies their definition by complementing it with the four basic properties of social mechanisms:

> *"First, mechanisms consist of component parts and their activities/interactions. Second, mechanisms produce something. Third, this productive activity depends essentially on the hierarchical (part–whole) structure of mechanisms. Fourth, mechanism explanations are representations or models of mechanism"* (Pajunen, 2008:1451)

These properties further exemplify that organizational mechanisms tend to be rather complex systems (Glennan, 2002:344). They consist of entities which reflect organizational life, such as departments and individuals, and which by interacting with each other produce the behavior or result the mechanism is bound to explain. According to a part-whole hierarchy, the entities can be differentiated as belonging to a higher or lower level of analysis. The lower level entities, which in organizational life often are individuals, activate the higher level to produce the focal result. Mechanisms therefore involve a connection between the micro and macro level (Hedström & Swedberg, 1996) which produces emergent behavior.

Building on our identified research focus, we argue that the input variables of our research reflect characteristics of the organizational environment whereas the output variables relate directly to organizational path dependence. As organizations react and adapt to their environments in learning processes,[27] our input and output variables are connected by a mechanism of learning. If learning provides a fit between an organization and its environment, path dependence resulting from learning effects shows as a maladaptation of the organization to its environment. Based on the above specified mechanism properties, in the following section we deal with the mechanism of learning as specified in path dependence theory and identify its parts and interactions which need clarification.

[27] See chapter 2.2.2 on learning as connecting organization and environment.

The mechanisms which create path-dependent outcomes are of a special type; they are self-reinforcing (Sydow, Schreyögg, & Koch, 2009). In self-reinforcement *"[e]ach step along a path produces consequences which make the path more attractive for the next round"* (Pierson, 2000:253). Specific actions or choices bring about a set of forces that encourage that action or choice to be maintained (Page, 2006:88). The self-reinforcing logic in learning in organizations is attributed to three different properties (Sydow, Schreyögg, & Koch, 2009:700).

First, with reference to the theory of learning effects, Sydow, Schreyögg, & Koch (2009:700) indicate that learning is accompanied by efficiency gains. The more often an action is performed, the more skillfully it can be carried out. The learner experiences an increase in efficiency, as for example, with decreasing costs per unit output (Argote, 1999). The increasing efficiency will make it ever more likely that the learner continues to enlarge his competences in the once chosen field. Second, Sydow, Schreyögg, & Koch (2009:700) claim that the self-reinforcing dynamic of learning effects impacts on different organizational levels. Here, they point to the well known tendency of exploitative learning crowding out explorative learning (March, 1991). Similar to individuals, organizations tend to improve existing skills instead of acquiring new ones.[28] Third, Sydow, Schreyögg, & Koch (2009:700) connect this dynamic to a related approach. Miller (1993) describes how organizations which concentrate on refining their success might become excessively focused and therefore increasingly simple concerning their worldviews, goals and strategies. Excessive simplicity can be the result of a self-reinforcing learning dynamic and must be considered an indicator for path dependence.

Sydow, Schreyögg, & Koch (2009:700) point out important properties of learning effects in organizations. But, as can be concluded from our definition of social mechanisms, these properties need further elaboration if we are to clearly specify the learning mechanism driving path dependence. We have to give a precise account of the elements of the mechanism and their interactions. This involves a specification which levels are involved in learning and which entities in organizational life constitute these levels. As mechanisms reflect a part-whole hierarchy, the learning processes acting on the different levels as well as the processes connecting the levels

[28] We deal with the concepts of exploitative and explorative learning in more detail in chapter 2.2.4.

have to be identified. The necessity of a clearer specification of the different levels and processes is further emphasized by Hedström & Swedberg's (1996:296-298) classification of mechanisms. Mechanisms can be considered to consist of different parts which together describe how the macro level links to the micro level of the mechanism and back. All three components of a mechanism described as situational, individual action and transformational are essential for understanding social dynamics.[29]

To specify learning effects in organizations, we have to consider which processes guide learning at the micro level in organizations, how this learning is transferred to the macro level and how the macro level again impacts learning on the micro level. The interaction of these processes is bound to shape the organization's adaptability towards its environment. Clarifying the elements and processes involved in the learning mechanism also brings us closer to a specification how to measure path dependence. Even if organizational path dependence generally is concerned with the dominance of suboptimal strategies, structures or beliefs, the identification of path dependence always depends on the research field and the underlying mechanism.

In the following chapter, we refer to the multifaceted field of organizational learning[30] to work out the above described missing aspects in the path-dependent learning mechanism.

2.2 Path Dependence and Organizational Learning

The large literature on organizational learning agrees that the ability of an organization to learn strongly affects its performance and, in turn, is vital for its survival and adaption (Berends & Lammers, 2010:1046; Argote, 2009:3). There are many differences concerning other aspects of learning. Learning takes place on different levels, occurs through various processes, and happens in different cognitive and

[29] Hedström & Swedberg (1996:296-298) build their classification of mechanisms on the macro-micro-macro model by Coleman (1986). Mechanisms which describe the macro-micro transition are referred to as situational. The connection between an individual's beliefs or action opportunities and his action on the micro level are described as individual action mechanisms. Transformational mechanisms, in turn, refer to the emergent outcomes on the macro level which results from micro level behavior.

[30] For a characterization of organizational learning as a complex and interdisciplinary topic see for example Argote & Miron-Spektor (2011:1) and Berthoin Antal et al. (2001:921).

behavioral domains (Dosi, Marengo, & Fagiolo, 2003:27-31). Collective learning has been analyzed at various levels: between organizations, at the organization level and at group level (Bunderson & Reagans, 2010:1). Research suggests a variety of learning modes differentiating between stages of a learning process, as the creation, transfer and retention of knowledge (Argote, McEvily, & Reagans, 2003), or the scope of learning involved, as is the case for incremental vs. radical learning (Miner & Mezias, 1996). Some studies focus on the cognitive features of organizational learning (Argyris & Schön, 1978; Daft & Weick, 1984) whereas others mainly consider its behavioural implications reflected in an organization's skills, routines, and capabilities (Levitt & March, 1988). A highly relevant distinction with respect to path dependence was made by approaches which concentrated on the dichotomous quality of learning to produce either stability or change (Hedberg, Nystrom, & Starbuck, 1978; March, 1991; Crossan, Lane, & White, 1999; Burgelman, 2002).

Building on the diverse organizational learning approaches, our aim in this chapter consists in elaborating the self-reinforcing learning mechanism in path dependence theory. For this purpose, we first define organizational learning with relation to its central components knowledge and experience. Second, we point out its central function in linking an organization to its environment. Third, we distinguish the different levels of organizational learning and analyze its dichotomous qualities of exploitation and exploration with respect to organizational path dependence. We finish the chapter by introducing a framework of path-dependent organizational learning which, subsequently, guides our analysis.

2.2.1 A Definition of Organizational Learning: From Experience to Knowledge

The diversified nature of organizational learning is a hallmark of this field (Argote, McEvily, & Reagans, 2003:571; Friedman, Lipshitz, & Popper, 2005:19-20; Argote & Todorova, 2007:194). But although organizational learning encompasses a large and varied literature there is common ground to most definitions of organizational learning (Scherf-Braune, 2000:10). Basically, organizational learning can be defined as *"a change in the organization's knowledge that occurs as a function of experience"*

(Argote & Miron-Spektor, 2011:2). A closer look at the concepts invoked by this definition allows us to grab the manifold nature of organizational learning and work out important characterizing features.

The concept of organizational knowledge is difficult to pin down. Changes in knowledge have been measured in relation to the performance of the organization (Epple, Argote, & Murphy, 1996; Argote, 1999; Macher & Mowery, 2003) or with reference to its product characteristics or patent stock (Helfat & Raubitschek, 2000). Others consider knowledge changes to become visible in the variation of practices, routines, or capabilities (Levitt & March, 1988; Teece, Pisano, & Shuen, 1997; Dosi et al., 1999; Dosi, Faillo, & Marengo, 2003) or to be reflected in a change in the cognitions of organizational members (Weick, 2002). Evidently, researchers have interpreted and measured knowledge in many different ways. Looking closely, we can distinguish between different domains of knowledge, different repositories, and different components.

Organizational learning literature has differentiated between learning as a change in the behavioral domain of an organization or as a change in its cognitions (Leroy & Ramanantsoa, 1997:871). Learning processes are supposed to change the conceptual schemes and interpretations among organizational participants or to be reflected in the actions of the organization (Fiol & Lyles, 1985:805-806). Still, the reasoning behind the different perspectives is in some ways similar.

The behavioral viewpoint suggests that organizational knowledge resides in the organization's social and physical artifacts like products, routines, or capabilities (Huber, 1991; Levitt & March, 1988; Daft & Weick, 1984; Nelson & Winter, 1982). Organizational knowledge arises from the experience and interactions of organizational members and, subsequently, is stored in the organization's routines and processes.

The cognitive viewpoint separates changes in the state of knowledge from changes in organizational behavior. It highlights that the results of learning are incorporated in the cognitions, beliefs and values of individuals and the organization (Fiol, 1994; Huber, 1991; March, 1991). Participants of organizations, working together, establish a dominant logic which roots in their shared history and guides managerial actions

(Tripsas & Gavetti, 2000:1148).[31] Both viewpoints refer to learning as a process in which experience is the basis for change and adaptation and which converts experience into possibilities for action. Thus, cognitive changes must be considered to be the core of learning and precede changes in organizational behavior (Huber, 1991; Weick, 1995).

The different domains of knowledge tie in closely with its different repositories and its different components or qualities. Levitt & March (1988) and March (1991) suggest that knowledge is embedded in an organization's routines and standard procedures, in its products and processes, in its technology and equipment, in its lay-out and structures as well as in its culture, norms and beliefs. Walsh & Ungson (1991:63-67) dealing with organizational memory identify five bins in which knowledge is retained, the participating individuals, the organization's culture, its standard operating procedures and practices, roles and organizational structure and the workplace ecology. For Starbuck (1992) knowledge resides in the individuals, the physical capital, the organizational routines, and in the culture of the organization. Although differing in some aspects, there seems to be common agreement as to the main loci of organizational knowledge (Argote & Darr, 2000:53-54). In general, individuals as well as organizational culture and routines are considered to be the key repositories storing organizational knowledge.[32]

Another important distinction refers to the tacit and explicit components of knowledge. Even if sometimes framed as a distinction between information and knowledge (Dosi, Marengo, Fagiolo, 2003:23) or between information and know-how (Kogut, 2008:50), researchers agree that there are different types of knowledge which can be distinguished according to their codifiability and their ways to transfer between participants in organizations. Tacit knowledge is abstract and difficult-to-articulate knowledge, it best transfers through personal interaction and observation. It can involve technical facets, in a sense of special skills acquired by a person, or cognitive

31 Hargadon & Fanelli (2002) differentiate between empirical and latent qualities of knowledge. The empirical perspective focuses on knowledge acquired as a function of experience whereas the latent perspective sees knowledge as a possibility to generate new actions. With this differentiation, the authors refer to the dichotomy in organizational learning as leading to stability or change with which we deal in chapter 2.2.4.

32 Which repositories of knowledge in organizations are acknowledged by scholars of organizational learning depends on their approach concerning the general ability of organizations to learn. We deal with this aspect in chapter 2.2.3 which is concerned with the different levels involved in organizational learning.

facets which are incorporated in implicit mental models. Explicit knowledge, in contrast, often refers to academic data that can be described in a formal systematic language. Examples include manuals, copyright or patents. (Dhanaraj et al., 2004:430; Argote, McEvily, & Reagans, 2003:574; Smith, 2001:314-315). The two sides of knowledge, therefore, reflect the implicit know-how dimension that is derived from face-to face contacts and the explicit know-what dimension that is readily communicated and can be stored in information-retrieval systems (Smith 2001:315).

Experience is the second concept invoked by our definition of organizational learning. Argote & Miron-Spektor (2011:4) claim that *"[l]earning begins with experience."* A person gaining experience makes an observation which is based on exposure to or involvement with another person, a thing or an event.[33] Similar to organizational knowledge, experience encompasses different dimensions which help us to better grasp its meaning. Most basically, the dimension direct vs. indirect experience refers to whether the experience was made by the focal unit or was acquired indirectly by learning from other units. Learning from indirect experience often is referred to as vicarious learning or knowledge transfer (Argote & Ingram, 2000). Argote & Miron-Spektor (2011:4) identify four other dimensions of experience in organizational learning research. The content dimension of experience reflects that experience can be acquired about different things or persons which in relation to the learning unit might have different qualities. For example, experience can be based on successful or unsuccessful task performance (Denrell & March, 2001), results from novel tasks or from tasks that are already well known (Levinthal & March, 1981). The temporal dimension of experience considers that experience can be acquired during or after task performance (Ellis & Davidi, 2005) and, more importantly, that it can differ in frequency and pace (Levinthal & March, 1981; Lampel, Shamsie, & Shapira, 2009).[34]

The main pillars of a definition of organizational learning, knowledge and experience, comprehend many different dimensions and highlight the multi-faceted nature of this research field. Organizational learning seems to derive its complex character mainly from the involvement of different levels in organizations. Experience encompasses

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33 See http://en.wikipedia.org/w/index.php?title=Experience&oldid=458507450.

34 Argote & Miron-Spektor (2011:5) add another dimension of experience which concerns the way the organizational learning scholar acquired its data. Experience, therefore, can also be differentiated if it occurs naturally or if it is simulated by experiments or computational methods.

observations made by the individual himself or resulting from the exchange with others. Knowledge is not merely retained by individuals but also by collective facilities as the organizational culture or routines (Walsh & Ungson, 1991:63-67). Daft & Weick (1984:285) point out that *"[t]he distinctive feature of organizational level information activity is sharing."* It is first of all the act of sharing knowledge between levels and individuals that enables the organization to learn.[35] But despite the complex picture of organizational learning due to its interacting organizational levels, in essence, organizational learning is a transformation process. It converts experience into organizational knowledge which again feeds back into future experience.

In the following chapter, we deal with organizational learning as connecting the organization to its environment and consider where in the transformation of experience into knowledge the organizational environment comes in.

2.2.2 Organizational Learning as Linking Organization and Environment

A common claim in organization theory is that organizations have to establish 'fit' with their surroundings in order to perform well (Miller, 1993:162; Burton, Lauridsen, & Obel, 2002). In contingency theory, congruence of structural and strategic factors with the task environment of the organization predicts organizational performance (Burns & Stalker, 1961; Lawrence & Lorsch, 1967; Thompson, 1967). In population ecology, organizational survival depends upon the fit between characteristics of the organization and its environment (Hannan & Freeman, 1977; 1984). Even if 'fit' is a central concept in these approaches, they are either not concerned with the processes leading towards 'fit' (as in the case of contingency theory) or these processes are attributed to selection forces on the population level (as in the case of population ecology). Organizational learning research, on the other hand, considers the 'fit' of an organization to its environment as emerging from processes internal to the organization. In organizational learning, the organization reflexively deals with its

[35] Daft & Weick (1984) differentiate between interpretation and learning. While in interpreting the organization attributes meaning to the data from the environment, learning is connected to actions taken based on the shared interpretation. We consider changes in the organizations values, cognitions, or beliefs to be sufficient for learning.

environment and as a result develops and substantiates its interpretations about it (Hedberg, 1981:3; Klimecki & Thomae, 1997:2). Consequently, effective learning is bound to show in the organization being well-adapted to its surroundings (Levinthal & March, 1993:105). This makes the ability to learn crucial for organizational survival (Teece, Pisano & Shuen, 1997:510; Dosi, Faillo, & Marengo, 2008:1166).[36]

Let us take a closer look where the environment enters the organizational learning process. In learning, the organization moves from experience to knowledge. For experience then to become knowledge on an organizational level, processes of sharing, selecting and aggregating knowledge are necessary.[37] Argote & Miron-Spektor (2011:2-3) argue that organizational learning is embedded in the environmental context[38] and that the environment shapes the experience the organization gathers. Daft & Weick (1984:285-286) point to a more active approach of the organization. In processes of scanning, the organization collects information about its environment. Even if Daft & Weick (1984:285) acknowledge the collective nature of organizational learning, as organizations aggregate knowledge and embed it in collective repositories, they point out that the individuals are the only means for the organization to scan the environment. Therefore it is individual experience which incorporates knowledge about the environment into the organization.

The next chapter is concerned with the individual and collective level in organizational learning and clarifies how individual learning is linked to organizational knowledge.

2.2.3 Individual and Organizational Levels of Learning

The multifaceted nature of organizational learning mostly results from the different levels in organizations which are involved in the learning process. Levitt & March

36 The debate on dynamic capabilities also points to the necessity of persistently altering existing competences to adapt to a changing environment. The rigidifying tendencies in learning are often overlooked in this context. For a discussion, see Eberl (2009), Schreyögg & Kliesch-Eberl (2007).

37 The different processes involved in organizational learning are dealt with in chapter 2.2.5.

38 The notion of context in Argote & Miron-Spektor's (2011) framework in addition to the environmental context also encompasses the organizational context. As organizational knowledge accumulates in the organizational context, past knowledge is supposed to affect future experience.

(1988:322) in this respect refer to the nested nature of learning which they consider responsible for the characteristic dynamic in organizational learning.

Basically, researchers in organizational learning distinguish between individual and collective levels. Speaking of collective or organizational learning, the question comes to mind who are the agents of learning? Does the organization learn or is it mainly a task of the organizational participants (Scherf-Braune, 2000:11)? The discrepancy arises as to how the organizational and the individual level are connected. Dosi & Marengo (2007:9), in this respect, distinguish between two different viewpoints concerning the nature of collective learning, a modular and a collective view.

In the modular view (Simon, 1991; Carley, 1992), organizational knowledge is just an aggregate of the knowledge of the individuals belonging to the organization.[39] Knowledge is only gathered and held by the individuals, the organization is not supposed to know something as an entity in its own right. Thus, for the modular perspective, organizational competencies are reducible to the skills at the individual level (Dosi & Marengo, 2007:9). Without organizational knowledge becoming incorporated in organizational repositories as routines or shared representations but only residing in the memory of individuals, the interaction between micro and macro levels in the learning system is lost. Individuals are merely influenced by interacting with their peers. The system-level emerges from the behavior of the individuals but is not an agent of learning in its own right. Thus, the modular perspective seems more concerned with the learning of individuals within organizations and less with the learning of organizations (Klimecki & Thomae, 1997:14). However, although individual learning is supposed to be a necessary condition (Argote & Miron-Spektor, 2011:4), it is not sufficient for organizational learning to occur.

The collective view (Hedberg, 1981; Winter, 1982; March, 1991) claims that organizational learning has a dimension which is not totally ascribable to the individuals in the organization. Knowledge is not just stored in the heads of the organizational members but also incorporated into a set of routines and shared representations which change as a result of experience (Dosi & Marengo 2007:9). Individual learning here is not sufficient but has to be embedded in a supra-individual

[39] Huber (1991:90), for example, argues along these lines when he claims that more organizational learning occurs if more organizational components acquire a specific knowledge.

component to become organizational (Levitt & March, 1988; Argote, 2009:9). Whereas in the modular approach organizational learning solely rests on the shoulders of the organizational participants, here the organizational level is involved in the learning process, too. The system level, represented by supra-individual repositories of knowledge as routines or other structures, has an active part in creating, transferring and retaining knowledge.[40]

Collective repositories of knowledge are made up of knowledge which is based on an interaction with the individual level. By sharing knowledge and interpretations, these repositories provide a *"thread of coherence"* (Walsh & Ungson, 1991:61) and can be agents of learning in their own right (Scherf-Braune, 2000:11-13).[41] Nonetheless, individual learning stays central for the learning outcome.[42] Walsh & Ungson (1991) in this respect conclude:

> *"Individuals are important not only because they, themselves, are a source of retained information, but also because they largely determine what information will be acquired and then retrieved from the other memory stores"* (Walsh & Ungson, 1991:78)

The individual is not only the central element for the acquisition of new knowledge; he also is deeply involved in transferring knowledge. We must not assume that knowledge can be directly transferred from one collective repository to another. It is retrieved from such a repository by the organizational participants possibly changed and then embedded in the same or another supra-individual structure. These processes involve different kinds of collective memory systems and have a more or less conscious character (Walsh & Ungson, 1991:69). The organizational level creates

[40] Nonaka (1994), for example, further distinguishes between group and organization level learning. For Argote, (2009:35) research on group and organizational learning seems to be converging so that the categorization of an entity as group or organization becomes more and more arbitrary. According to Argote (2009:35-36), definitions of groups and organizations have important similarities. They share a focus on the interaction and interdependence of individuals who work together on a common goal (e.g. Porter, Lawler, Hackman (1975:69) for organizations as well as Berdahl (1998) and McGrath, Arrow, & Berdahl (2000:95) for groups). Other features have lost their characterizing role as groups become more and more geographically dispersed and organizations tend to be less long-lasting and less differentiated. To conclude, organizational and group learning both involve the same learning processes and are distinct from individual learning. According to Argote (2009:34) organizations and groups learn from their individual participants and are involved in sharing and distributing their knowledge across individuals.

[41] For a critique of collective approaches to organizational learning see Friedman, Lipshitz, & Popper (2005:22-23).

[42] For a comparison of the different viewpoints concerning the role of the individual in organizational learning see Berthoin Antal et al. (2001:922).

knowledge by collecting and recombining knowledge that was incorporated into the organization by its participants. But it is the individuals who are able to gather knowledge based on their direct experience. Knowledge creation on the individual level, thus, involves experiential learning. Of course, individuals exchange knowledge with other individuals and have the possibility to learn from knowledge already held in the organization, but it is their potential to learn from direct experience, not from the experience of others, which clearly distinguishes the individual from the organizational level. March (2010) emphasizes the importance of experiential learning:

> *"[E]xperiential learning continues to be seen as one of the more important sources of adaptation in human action, a mechanism to improve the fit of actions by individuals or organizations to the environment they face."* (March, 2010:10)

His statement points to two interesting characteristics of experiential learning: Experiential learning is conducted by individuals but can be beneficial for organizations and experiential learning links the learning entity to its environment.

We will see in the next chapter that experiential learning is a central factor when dealing with the dichotomous qualities of learning. Learning has the possibility to induce change but it also leads to rigidities. This tension unfolds between the cumulative character of learning based on a history of experience and the way how learning links the organization to its environment.

2.2.4 Organizational Learning between Stability and Change

Learning processes provide 'fit' between an organization and its environment, but they also bring the lessons of history to bear upon the organization thereby limiting its scope of adaptability (Fiol & Lyles, 1985:804; Argote & Greve, 2007:338-339). Scholars of organization studies since long acknowledge that organizations have the tendency to improve already existing competencies even to a point where it is harmful for the organization (Kogut & Zander, 1992; Lomi, Larsen, & Ginsberg, 1997). The once successful core-competence turns into a core-rigidity (Leonard-Barton, 1992). Refining existing competencies provides increases in efficiency which lure the organization away from experimenting with alternative solutions. Organization learning research thus identifies two manifestations of learning which either create continuity or change. Learning can proceed in incremental steps that generate efficiency gains and finally lead to stability or it involves discontinuous jumps that result in major alterations.

The most prominent analytical constructs referring to the distinction between processes which tend to preserve a system's given form and processes which change the system are exploitation and exploration[43] (Caldart & Ricart, 2007:108). Exploitation refers to activities as refinement, efficiency and selection whereas exploration relates to experimentation, flexibility and innovation (March, 1991:71). For successful organizational learning, both learning modes are required, realizing the efficiency gains from exploitative learning and maintaining flexibility to deal with changes in the environment. Balancing exploitation and exploration is often bound to fail as exploitation is thought to crowd out exploration.

Eberl (2009:114-115) points out that the crowding out of exploration through exploitation is at the core of the path-dependent development of organizational competencies. The interaction of exploitative and explorative learning is complex and involves different processes on the individual and organizational level.[44] In the following, we draw on four prominent approaches dealing with the twin concepts in organizational learning. These approaches agree on many of the central features of the conflictive forces and consider exploitation crowding out exploration the decisive dynamic in organizational learning (Hedberg, Nystrom, & Starbuck, 1976; March, 1991; Crossan, Lane & White, 1999; Burgelman, 2002). Still, each approach emphasizes different aspects of the crowding out dynamic, looking at it from different angles, and therefore supplements March's (1991) explanations.

As outlined in chapter 2.1.5, path dependence theory refers to three properties of learning effects. Learning involves efficiency gains. It happens at different levels in organizations and learning in organizations involves an increasing simplicity in organizational goals and strategies. Dealing with the crowding out dynamic in

[43] The twin concept of exploitation and exploration is introduced in March (1991).

[44] Gupta, Smith, & Shalley (2006) give an overview of the open questions on exploration and exploitation which also highlights the complexity of the processes at different levels of analysis.

organizational learning helps us to grasp the missing elements and their interaction in the self-reinforcing mechanism of path-dependent learning.[45]

2.2.4.1 Exploitation and Exploration

The process of experiential learning is at the core of what was later named "*exploitation*" by March (1991:71). Positive experience with a procedure can lead to a competence based learning cycle. Procedures which generate favourable outcomes are more frequently applied leading to a further increase in competence with these procedures which in turn leads to even better results. Even if the incorporation of knowledge into memory works differently for organizations and individuals, both improve in things done frequently and successfully while losing competence in things done infrequently and with less success (Holmqvist, 2004:71). This elaboration of competences and the increase in routine work inherent in processes of exploitation also provides the organization with reliability in experience. Holmqvist (2004) defines exploitation as follows:

> *"The mechanism is one of mutual positive feedback between experience and competence, where retrieved portions of the past have a controlling effect on what organizations experience and thus continue to learn from."* (Holmqvist, 2004:71).

Exploitation, consequently, leads to a consolidation of experience. Levitt & March (1988:322) even refer to the resulting stable behavior as a competency trap. In their article, Levitt & March (1988) already discriminate between transforming a routine in a process of exploitation and choosing between different routines in the sense of alternative development trajectories. They point out that exploitation can lead to maladaptive specialization as experimentation with alternatives decreases in attractiveness:

> "*Since they convert almost chance actions based on small differences into stable arrangements, competency traps result in organizational histories for which broad functional or efficiency explanations are often inadequate"* (Levitt & March, 1988:323).

45 See chapter 2.1.5 for an explanation of learning effects in organizational path dependence theory.

Explorative learning, as a process in its own right, which balances the tendencies of exploitative learning, does not enter organizational learning theory until March's (1991) seminal article. March (1991) and Levinthal & March (1993) characterize exploration as a counterbalance to exploitation. Whereas exploitation refers to incremental improvement and increases in reliability in experience, exploration deals with radical changes and increases in variability in experience (Holmqvist, 2004:71). In explorative learning, the organization gathers knowledge unrelated to its current areas of competence. Exploration involves searching for and experimenting with unknown alternatives. Exploration does not build on existing organizational competencies and often its consequences are not tightly coupled to the actions taken which possibly obscures feedback. Consequently, exploration is a risky process, its results are essentially uncertain. (March, 1991:73; Levinthal & March, 1993:103-104).

March (1991) argues that balancing exploitation and exploration is essential for the survival of organizations. But achieving this balance is a difficult task. Organizations have to divide their attention and resources between both learning activities. The vulnerability of exploration, as March (1991:73) refers to it, builds on the dynamics and characteristics of the experiential learning processes. With the gains from exploitative learning being more certain and closer in time (March, 1991:73), explorative learning often is suppressed for the benefit of exploitative learning.[46]

In addition to these basic qualities of exploitative and explorative learning, in the following chapter we consider additional aspects to improve our understanding of the crowding out dynamic in organizations. First, crowding out of exploration happens as a consequence of the interaction of learning on the micro and macro levels in organizations. Second, its dynamics can be interpreted in terms of variation and selection processes at these levels.

[46] Traps brought forth by excessive exploration are less common but according to Levinthal & March (1993:105-106) can be caused by a dynamic of failure. The risky explorative learning involves a higher possibility to show unsatisfactory results which might then set in motion new search and change. Not only is the risk for failure higher when searching for innovative ideas but often the potential of new ideas is only realized after some experience with them has been accumulated. The organization thus become trapped in a *"cycle of failure and unrewarding change"* (Levinthal & March, 1993:106).

2.2.4.2 Crowding Out in the Interaction of Organizational Levels

Levitt & March (1988:320) emphasize that the experiential lessons of organizational members are incorporated in organizational routines which give the learning process a character less guided by consequentiality but more by legitimacy and appropriateness. Routines act as a collective memory and store the experience gathered by the organizational participants. By processes of socialization and instruction, the collective understanding of history is transferred to the individuals in the organization (March, 1991). The learning cycle feeds back into its beginning when the interpretations of the past become a frame within which future individual learning takes place.

Crossan, Lane & White (1999:524) give a more elaborate account of the tension between exploitation and exploration as evolving from the interaction between different levels of learning. In their 4I framework, they specify four sub-processes which connect individual, group and organizational level: intuiting, interpreting, integrating, and institutionalizing. Moving from intuiting to institutionalizing processes knowledge from the individual level to the organizational level, whereas moving from institutionalizing to intuiting brings organizational knowledge to bear on individual knowledge acquisition. Intuition happens at the individual level, it refers to the way in which individuals acquire new knowledge. In contrast to March (1991), Crossan, Lane, & White (1999: 526-528) emphasize the individual learning process as they distinguish different ways of intuiting. Intuition can be framed by previous experience and collective mental models and then is referred to as expert intuition, or it can create new insights if learners distance themselves from the existing patterns of knowledge, as is the case in entrepreneurial intuition. The second process, interpreting, extends from individual to group level when individuals exchange their intuition and derive a shared understanding. Integrating further continues the process of developing shared meaning on the group level. Its focus is on providing a basis for coherent collective action. Institutionalizing, finally, incorporates individual- and group-level learning into organizational level routines and structures, thereby revealing itself to be the characteristic feature of organizational learning (Berends & Lammers, 2010: 1047).

The four processes make up a learning loop in which the experience of the organizational members feed back into individual intuitions (Lawrence et al., 2005:181). The learning cycle is divided in two main flows. The feed forward process which incorporates individual ideas into the collective level moves from interpreting to integration and is related to exploration. The feedback process moves from the organizational to the individual level as organizational knowledge residing in time-honored routines and structures impacts knowledge acquisition on the individual level. The feedback process is considered to be exploitative in character.

The framework of Crossan, Lane, & White (1999) emphasizes important aspects in organizational learning. Individual learning is the origin of new ideas or exploration, whereas the organizational level is an important driver of exploitation. Still, we have to be careful to equate all feed forward processes with exploration in the sense of inserting innovative ideas into the organization. The effectiveness of individual learning is bound to develop in close interaction with the organizational level. In the following section, we deal with the evolutionary aspects of the crowding out dynamic. Considering the interplay of the different levels in terms of variation and selection processes helps us to better understand its impact on the adaptability of the organization.

2.2.4.3 Crowding Out as Processes of Variation and Selection

Crowding out processes have been described in relation to the variation in knowledge held in the organization. Hedberg, Nystrom, & Starbuck (1976:49) argue that in response to its perceptions of the environment, an organization hones its procedures and develops a standardized action repertoire that efficiently focuses perceptual and problem-solving capacities. As heterogeneity declines, the ties between the organization and its environment loosen. March (1991), in his model, similarly implies that the organizational capability for change is directly connected to the differences in beliefs existing in the organization.

Burgelman (2002) in his study of Intel explicitly describes the dynamic of crowding out with relation to evolutionary processes at firm level.[47] Organizational strategy making here is conceived as *"an organizational learning process based on internal experimentation and selection"* (Burgelman, 1991:255).

Using the perspective of an intra-organizational ecology of strategy-making, Burgelman (1991; 2002) describes the interaction between induced and autonomous strategy processes. An organizational strategy here is conceived to drive an organization's competences, its goals and outlines its action domain.[48] Burgelman points to an important aspect concerning strategy at the organizational level. Here, a strategy serves as an internal selection mechanism which provides a structural context guiding and framing actions on lower levels. Burgelman considers it the task of the top management to provide this sort of coherence. The lower level in organizations, on the other hand, has the potential to act as an important source for variation. Burgelman (1991; 2002) predominantly considers the middle management, endowed with specific goals and perceptions, to come up with new strategic initiatives. The levels are connected by different processes which feature different adjustment and renewal capacities. These are categorized in terms of their impact on the variation of activities in the organizational system.

The induced strategy process which works top down aims at bringing the organizational level of strategy to bear upon the strategic initiatives of middle management. It is therefore considered a variation reducing process but not in the sense that it completely suppresses development. It provides focus to organizational activities. Activities are bound to be planned variations, as for example the development of existing product families and core technology advances (Burgelman, 1991:245-246).

The autonomous strategy process in turn works bottom up. Individuals in the organization try to introduce activities which are outside the scope of the current organizational strategy; it is therefore a process which increases variation. As these

[47] Organizational learning theory as well as evolutionary economics are both direct descendants of 'A behavioral theory of the firm' (Cyert & March, 1963). They thus share a common emphasis in basic assumptions (Nelson & Winter, 2002:25) and experience some integration of ideas (Argote & Greve, 2007:338).

[48] Burgelman (1991:243) describes strategies as technical, economic, and cultural prescriptions and rules which direct strategic action.

activities are often triggered by the observation of events external to the organization, the autonomous strategy process is driven by organizational levels with direct contact to the organizational technology and market environment, mostly significantly below top management. An important part of the process refers to aligning new ideas with the existing organizational strategy. The ideas emerging from autonomous strategy processes thus need to demonstrate their viability in the internal selection environment.[49] Although autonomous ideas are hard to suppress, it is this evaluation and alignment process which often hinders them from leaving their mark in the organization.

The intra-organizational ecology perspective (Burgelman, 1991; 2002) is useful to highlight the interaction inside the organization in terms of the variation and selection of ideas. Concerning the selection of ideas, Burgelman (2002) claims that it is vitally important for an organization that its structural context, as it is shaped by the organizational strategy, reflects the selective pressures of the environment. With relation to the variation of ideas, Burgelman (2002: 351-352) does not merely imply that decreasing variation in ideas interferes with the organizational adaptability. In Burgelman's locked-in organization, there can be continued variation which does not come to bear on the organizational knowledge. The crowding out dynamic, here, does not affect the ability of the middle management to perceive new solutions in the environment. Similarly, Hedberg, Nystrom, & Starbuck (1976:49) show that events which point to changes in the environment can still be perceived inside the organization. Additionally, in their approach they do not trigger behavior in the organizational domain since they cannot be related to the usual activity repertoire. In consequence, both approaches imply strong learning processes at the individual level which incorporate variation into the organization. The effects of the variation on the lower level for organizational learning depend on the interaction with the organizational level.[50]

We conclude that organizational learning involves the interaction of exploitative and explorative modes of learning. The twin concepts have been described in terms of the

[49] Obtaining resources for advancing autonomous activities in the internal selection environment is described by the author as a demanding and often political process which involves repeated interaction from managers of different levels (Burgelman, 1991:246-248).

[50] March's (1991) model, in contrast, does not feature processes of individual learning.

qualities of the different learning modes, as consequences resulting from the interaction of different levels in organizations and with respect to the variation and selection dynamics involved in the accumulation of knowledge. In each approach, exploitation is supposed to refine the knowledge base or skills of the organization whereas exploration is considered to question the existing framework. Both learning modes are considered necessary for the survival of the organization (Lavie, Stettner, & Tushman, 2010:113). Still, the tension between the two learning gestalts is a core aspect in almost all approaches[51] and is regarded to mostly work in favor of elaborating existing competencies (Holmqvist, 2004; Leonard-Barton, 1992). The dynamic of exploitation crowding out exploration is a result of positive feedback processes in which positive experience in a specific domain leads to an inclination to accumulate even more competence in the respective domain. The competence increasing learning cycle holds for individuals and organizations alike but in organizational settings it is connected to the interaction between individual and organizational level. Whereas the individual organizational member is supposed to increase his competencies by experiential learning, the organizational level conceived as the organizational layer of strategy, organizational rules, culture or similar organizational knowledge repositories creates collective understanding by selecting and integrating individual knowledge. On the organizational level therefore, the process of crowding out refers to reducing the variation of ideas on the individual level or limiting their impact on the organizational level.

With the crowding out dynamic at the heart of organizational learning we notice an interesting aspect with relation to path dependence theory. In organizational learning, lock-ins must be considered an indispensable element. Or as Dosi, Marengo, & Fagiolo (2003:64) point out: *"one should expect inertia and 'lock-in' to be indeed one of the corollaries of the very fact that 'agents have learned'."* On the other hand, the crowding out dynamic is what constitutes organizational competences in the first

[51] Argyris & Schön (1978) differentiate between two learning modes, single-loop and double-loop learning. Single-loop learning leads to an adaptation of the organization to existing goals and norms (Schüerhoff, 2006:85), as it tries to improve organizational performance with reference to the existing measuring bars. Double-loop learning questions the existing norms for performance and possibly modifies the organizational theory-in-use. Argyris & Schön (1978) imply that the relationship between single- and double-loop learning is one of processes of different quality with double-loop learning being the superior one. In the literature, this proposition is criticized with reference to the different temporal weights attached to processes which are either concerned with refinements in an existing framework or with revisions of this framework (Ghemawat & Ricart I Costa, 1993:61).

place. Without exploitative learning in which knowledge is refined and adapted to the organizational surroundings, the development of organizational competences is impossible (Eberl, 2009:114-117). Dealing with the dynamic of crowding out, we have to take into consideration its two-fold nature. If and when it is bound to be problematic for the organization necessarily depends on the interaction of the different learning processes involved in this dynamic and the requirements of the organizational environment.

In the following section, we build on the conclusions of the preceding chapters and integrate them into a theoretical framework. Path dependence theory emphasizes learning effects as an important mechanism driving organizational paths but fails to give a precise account of its working. The lower and upper level elements, according to the part-whole hierarchy of social mechanisms, as well as their detailed interaction remain underdeveloped. Our framework aims to explicate the self-reinforcing learning mechanism leading to organizational path dependence by explicitly pointing out the nature of individual learning and how it is embedded in organizational settings.

2.2.5 A Theoretical Framework of Path-Dependent Organizational Learning

Crossan, Lane, & White (1999:523) argue that *“[a] framework defines the territory.”* It specifies the phenomenon of interest, the key premises as well as the relationship between the elements of the framework. Our phenomenon of interest is the unfolding of organizational path dependence in different environmental conditions. With relation to our key premises, we consider learning as the most important mechanism linking an organization to its environment. In our definition of organizational learning, we assume that knowledge evolves from past experience and that organizational learning involves different levels. Furthermore, we assume that learning involves a dichotomy of learning modes which can be interpreted in terms of different qualities and dynamics. As a result, the elements of our framework basically build on our definition of knowledge and incorporate the different levels of learning. Their relationship specifies organizational learning as involving two feedback loops, one on the individual level, the other connecting organizational and individual level.

The theoretical framework for self-reinforcing organizational learning is shown in Figure 3. It aims at making the self-reinforcing tendencies in learning as well as the interaction between different levels of learning more explicit. In dealing with the path-dependent characteristics of organizational learning it gives a realistic outlook on the scope and intelligence of organizational learning.[52]

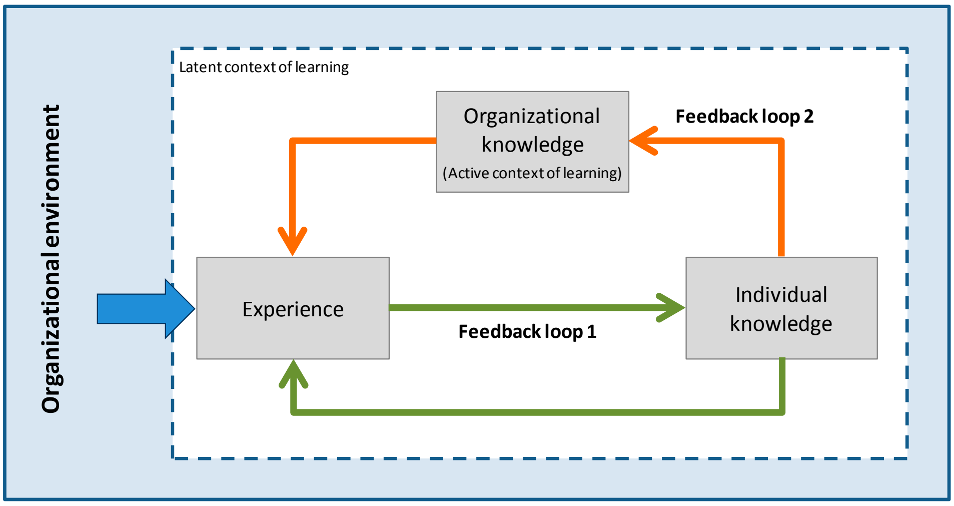

Figure 3: Theoretical framework of self-reinforcing organizational learning
(adapted from Argote & Miron-Spektor, 2011:3;
Argote & Todorova, 2007:196; Lavie, Stettner, & Tushman, 2010:111)[53]

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52 A growing literature calls for flexibility and fluidity of organizational forms and behavioral features (Eisenhardt & Martin, 2000; Brown & Eisenhardt, 1997; Teece, Pisano, & Shuen, 1997). The increasing emphasis on flexibility has led to problematic requirements concerning organizational learning. Calls for fluidity and flexibility today are often answered by endowing the organization with capabilities which are in a constant state of flux. Organizations with these dynamic capabilities are closely coupled to their environments; they constantly acquire knowledge about different options without this knowledge becoming embedded in higher levels of organizational learning (Eisenhardt & Martin, 2000:1113). This is problematic for two reasons: Capabilities are a product of collective learning. First, they are therefore subject to increasing returns in knowledge acquisition and second, they develop as a result of learning in a system of learners, which reflects the institutional dynamics of learning. They neither allow jumping from one field of competence to another, which would raise the question how competence can be developed in the first place, nor can they be understood as knowledge held by isolated organizational members. The exploitative half of the twin processes of learning reflects the characteristics of learning which have been overlooked here. Approaches favoring dynamic capabilities are not only difficult to conceive because they simply ignore very real tendencies in organizational learning processes, they moreover confront the organization with a serious dilemma. They strip the organization of processes which provide coherence and identity (Schreyögg & Kliesch-Eberl, 2007; Eberl, 2009; Schreyögg & Sydow, 2010:1252).

53 Please note that throughout the figures in this dissertation we use similar colors to refer to the two feedback loops as described in the theoretical framework. Individual learning dynamics are highlighted in green, whereas the learning dynamics involving the organizational level are marked in orange.

The Organizational Context of Learning

In general, learning is a process which develops over time. Experience is transformed into knowledge which again feeds back into future experience. Learning takes place in an organizational context which points to the fact that the learning processes are moderated by various organizational features. For example, the network structure of the organization or its culture influences how the learning process unfolds. Argote & Miron-Spektor (2011:3) in this respect distinguish between active and latent organizational context which differ from another in their capability for action. While the latent context merely influences the learning process, learning happens through the active context. This differentiation goes back to McGrath & Argote (2001), where the active context comprehends the organizational members, tasks and tools and their networks whereas the latent context refers to conditions which impose on the active context. For instance, contexts where members trust each other have been found to promote knowledge transfer in the organization (Levin & Cross, 2004). Lavie, Stettner, & Tushman (2010:118) in their framework on exploration and exploitation refer to similar aspects; the organizational antecedents or organizational features, as size, age, culture, determine if the organization tends to exploit or explore.

In accordance with a collective view on organizational learning, in our framework we consider the active context of learning to involve the supra-individual knowledge repositories which lend coherence to the organizational activities and thus are actively involved in the learning process.[54] We therefore refer to the active context as the organizational knowledge.

First Feedback Loop: Learning at the Individual Level

The first feedback loop in our framework describes the competence-increasing learning of the individuals in the organization. Arthur (1993) dealt with the path-dependent characteristics of individual learning. He notices that if the optimum is

[54] Argote & Miron-Spektor (2011:3) claim that knowledge is also embedded in the latent organizational context. While this is certainly correct, here we differentiate between active and latent context also with respect to their knowledge embedding capacity. A latent organizational context which is changed by the learning process would point to another feedback loop in the model. This can also be considered a possible extension to the model we propose later. We discuss the limitations and possible extensions of our model in chapter 7.3

difficult to identify, the agents often lock-in on suboptimal solutions. Starting from this indication, Ackermann (2003:242-245) identifies two essential characteristics which constitute the path-dependent nature of individual learning. First, individual learning is more than history-dependent, new experience is always interpreted in the light of previously acquired knowledge. Individuals, therefore, follow a learning trajectory. The derived mental models of individuals constitute a system of beliefs. The interrelatedness of the components of these thought systems or mental models makes refinement of an already existing framework much easier than the development of something completely new. Ackermann (2003:243) here alludes to complementarity effects on the level of mental models.

The second feature of individual learning which results in path-dependent behavior lies in a selective perception of the environment. Individuals are only able to consider small parts of their reality. This is bound to lead to inefficient results of learning which nevertheless are maintained by the learners. Consequently, individual learning starts out as a contingent process which soon exhibits inflexible behavior due to the above mentioned characteristics. Individual learning does not lead to a correct or objective view of the world. Due to the inflexible nature of the process and the limited perception of the learners, their misjudgments do not get corrected (Ackermann, 2003:244, Castaldi & Dosi, 2004:3). This process is captured by the first feedback loop in the framework. The individual knowledge feeds back into the beginning of the learning process; it affects the experience which is acquired by the learner.

Second Feedback Loop: Learning involving the Organizational Level

Individual learning captures merely one aspect of learning in organizations but not the one which makes learning organizational; it is necessary for organizational learning but not sufficient. (Argote& Miron-Spektor, 2011:4). On the level of the system, mere individual learning does not result in path dependence. With relation to path dependence, isolated individual learners would each end up with their own specific mental models based on their subjective experience. Learning becomes organizational only if we add the social context of learning (Ackermann, 2003:244). Organizational learning is a socially embedded process (Castaldi & Dosi, 2004:21). Interaction and communication in systems of interconnected individuals bring individual beliefs closer together. In social contexts, individuals not only learn from their own experience but also from the experience of others (Argote & Todorova, 2007:194-198).[55] Knowledge is thus incorporated on an organizational level which in our framework is reflected by the active context of learning and, from there, feeds back into the individual learning process.

The Environmental Context of Learning

In organization research, environments often have been specified in terms of their objects or their attributes (Bourgeois, 1980:33).[56] In the first category, the organizational environment is thought of as being composed of several constituent elements (Suarez & Oliva, 2005:1019). Organization ecologists (Bourgeois, 1980; Dill, 1958), for example, structure the environment according to the directness of its influence on the organization and distinguish between a task environment and a general environment. Whereas the task environment contains customers, suppliers, and competitors which directly impact the organization, the general environment encompasses the bigger picture, the demographic, social, and economic factors. In strategy research, the organizational environment is structured according to five forces encompassing, for example, bargaining power of suppliers and customers as well as competitive rivalry (Porter, 1979). In general, the environment can be defined as *“the pattern of all external conditions and influences that affect its [the organization’s] life and development”* (Andrews, 1971:48).

To depict environments in terms of their attributes, researchers have to further abstract from the environmental objects and consider the super ordinate characteristics that describe the state of the environment. In our framework, the organizational

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55 We will see in chapter 6.3 that it is precisely this feature which makes organizations surprisingly intelligent in deciphering their environments.

56 Bourgeois, (1980:33-34) points out that another category defines environments as perceptions and raises the question whether the objective or the perceived environment has more relevance for an organization. According to Weick (2002:S8), learning is perceptual. It is through perceptions that the environment becomes known to the organization. In accordance with Bourgeois (1980:35), we conclude that *“[e]very firm has an objective environment which places constraints on the way it operates”* but what the learners know about their environment depends on their perceptions. They are not able to comprehend its full complexity, nor are they able to set themselves free of their already acquired experience. Their cognitive patterns or maps work as a framework for interpreting experience and, thus, guide knowledge acquisition (Schreyögg & Sydow, 2010:1253).

environment affects the experience the organization gathers.[57] As we consider experience to be rooted in an observation based on an action, the environment specifies the action outcome relationships and consequently encompasses the pool of possible experience (Siggelkow & Rivkin, 2005:103). In this concept, the constituent objects of the environment are reflected only implicitly. What is relevant is their impact on the information the firm needs to gather (Siggelkow & Rivkin, 2005:103). Basically, we consider the environment to link potential organizational actions to outcomes and, thus, to provide feedback for the learning individuals. Based on this feedback, the organization is supposed to increase its understanding of the environment. The environment is therefore also the base of reference for the application of normative criteria such as for example the learning success.

Path dependence research points out that a base of reference is crucial for diagnosing path dependence (Sydow, Schreyögg, & Koch, 2009:695). Sydow, Schreyögg, & Koch (2009:695) claim that determining a lock-in as inefficient[58] requires a comparison with other possible solutions. This can already be shown with relation to Arthur’s model (1989). Here, inefficiency is defined in terms of agents experiencing regret. In the case of an inefficient market outcome, there are agents who could have been better off if the neglected technology had been developed equally. The technologies and their return functions referring to how strong its pay-off increases with the number of adopters are exogenous factors for the agents. To determine if a market outcome is inefficient in the specified sense, we have to compare it with other market outcomes which would have been feasible under the particular technological conditions. In this model, the base of reference consists of the technological conditions; from them we derive the pool of possibilities for a comparison with the achieved outcome. In our case, the organizational environment provides the base of reference for the learning process. Inefficiency can be determined with relation to how well the organizational knowledge reflects the state of the organizational environment. In the subsequent chapter, we define the relevant attributes of organizational environments for our research focus and introduce different environmental scenarios.

[57] On the connection between organization and environments see chapter 2.2.2.

[58] On the properties of path-dependent processes see chapter 2.1.2.

2.3 Specifying the Environmental Context: Complexity and Turbulence

In our theoretical framework, we showed the path-dependent nature of learning as described by the two feedback loops and exemplified the role of the organizational environment in the learning framework. We outlined that for learning not a detailed portrayal of the organizational environment is relevant but that the environment is characterized in terms of the information the organization has to collect. In this chapter, we therefore consider which attributes are most relevant for such a super-ordinate description of the environment.

Environmental complexity and turbulence are among the most prominent features in categorizations of organizational environments. In their review of the organizational environment literature, Sharfman & Dean (1991) claim that throughout the literature, complexity and instability and, as a third category, the availability of resources have been used to portray organizational environments.[59] Complexity and turbulence not only belong to the most widely used attributes to describe environments they also are of special relevance for an inquiry into the effects of the context on organizational path dependence. Several studies inquiring into path dependence indicated the significance of environmental complexity for the development of paths (North, 1990; Pierson, 2000; Koch, Eisend, & Petermann 2009).[60] In these approaches, environmental complexity is even considered to be a necessary precondition for path-dependent results (North, 1990) or to increase their likelihood (Pierson, 2000). In the unfolding of path dependence due to a mechanism of learning, environmental complexity is bound to play a significant role which probably exceeds that of an enhancing context.[61] Crouch & Farrell (2004) in their extended Polya urn model indicated the relevance of environmental turbulence for the development of paths. Dormant resources here leave room for counteracting the impending path dependence and bear a close resemblance to the variation of ideas in organizational learning

59 Burton & Obel (1998:167-171) in their literature review on measures of the environment arrive at a similar conclusion.

60 Chapter 2.1.4 deals with the role of the environment in studies of path dependence.

61 Sydow, Schreyögg, & Koch (2009:701) claim that complexity of the context is neither a necessary nor sufficient condition for path dependence.

approaches (March, 1991; Burgelman, 2002).[62] It seems plausible that characteristics of the change, such as its timing and scope, are highly relevant for the organization since these might be able to distract the organization from its learning path.

The following table provides an overview of conceptualizations of environments with respect to the three aforementioned attributes identified by Sharfman & Dean (1991) and shows how these attributes have been addressed in the literature.

	a.) Complexity	b.) Dynamism, stability	c.) Resource availability
March & Simon (1958)			Munificence
Emery & Trist (1956)	Complexity, routineity	Instability	
Thompson (1967)	Heterogeneity	Dynamism	
Child (1972)	Complexity	Variability	Illiberality
Duncan (1972)	Complexity	Dynamism	
Mintzberg (1979)	Complexity, diversity	Stability	Hostility
Aldrich (1979)	Concentration, heterogeneity	Stability, Turbulence	Capacity, consensus
Tung (1979)	Complexity, routineity	Instability	
Lawrence (1981)	Complexity	Unpredictability	
Dess & Beard (1984)	Complexity	Dynamism	Munificence

Table 2: Conceptualizations of environments
(Source: Sharfman & Dean, 1991:683, approaches appended)

Thompson (1967:72) employed a two-dimensional measure to characterize the environment. Heterogeneity in contrast to homogeneity refers to the similarity between the environmental elements whereas dynamism in contrast to stability describes unpredictable change of the elements. Child (1972:3-5) starts with similar features which he names complexity and variability and appends another characteristic. His notion of illiberality builds on the availability of resources in the

62 See chapter 4.1.1 on the dynamic of decreasing internal belief variety

environment and has a similar meaning as March and Simon’s (1958:120) munificence. In Mintzberg’s (1979: 267-269) framework, the term diversity reflects Thompson’s (1967:72) heterogeneity and Child’s (1972:3-4) complexity while adding a new aspect. Here, complexity also describes the degree of sophisticated knowledge necessary to conduct business in a given environment. His notion of environmental hostility involves the availability of resources, which is similar to Child’s (1972) illiberality, and the competition for resources. Aldrich’s (1979:63-70) dimensions approximately resemble Child’s (1972) framework. Still, turbulence in his approach reflects unpredictability based on environmental interconnections. Generally speaking the three categories throughout the literature are conceived as:

> *“(a) the degree to which the number and sophistication of elements in the environment make understanding it more difficult, (b) the stability/predictability of an environment, and (c) the level of resources available in an environment relative to the number of firms competing for those resources.”* (Sharfman & Dean, 1991:684)

But despite many similarities in the described frameworks, there are also notable differences. We deal with these in the following and provide a specification for the environmental dimensions in this work. The third dimension, referring to the availability of resources, although an important one for scenarios of inter-organizational learning will be dropped as our focus is not on competing organizations. For a perspective of learning processes internal to the organization, the instability of the environment and its complexity are the decisive features.

A good starting point for a discussion of the environmental attributes is the still popular description by Lawrence (1981):

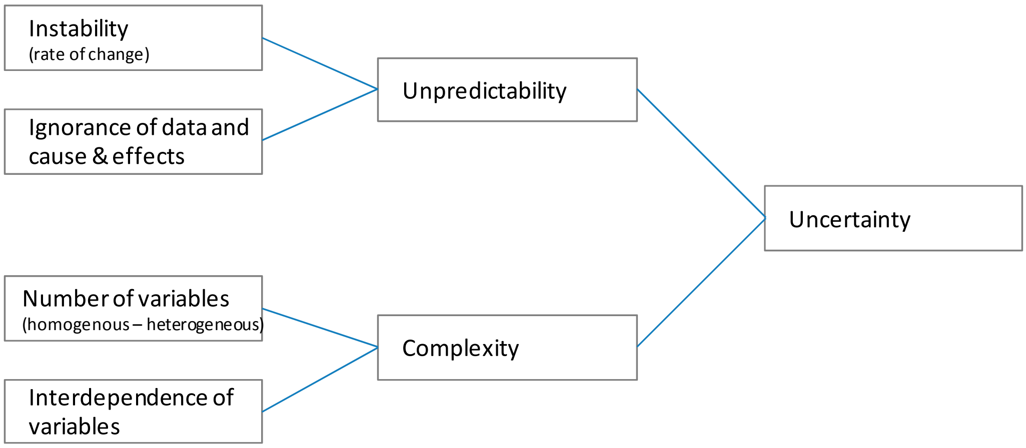

Figure 4: Descriptors of the organizational environment
(Source: Lawrence, 1981:316)

Environmental uncertainty here is specified as being composed of unpredictability and complexity which again involve several features. Complexity consists of the number of environmental variables as well as their interdependence. Unpredictability in this framework consists of the instability of the environment or its rate of change and the ignorance of cause and effects. Environmental change, or so it seems, despite its many different labels, has been understood in a quite consistent way (Siggelkow & Rivkin, 2005:103). Eisenhardt & Bourgeois (1988:816), for example, specify a high velocity environment as one *"in which there is rapid and discontinuous change in demand, competitors, technology and/or regulation, such that information is often inaccurate, unavailable, or obsolete."* Wholey & Brittain (1989:867-869) in their framework on longitudinal environmental change focus on similar aspects, the frequency and amplitude of change, and add one more attribute, the predictability of change. Their notion of predictability somehow reflects Lawrence's (1981) measure of ignorance of cause and effects. Siggelkow & Rivkin (2005:103) conclude that under different labels environmental change has been framed in similar ways. *„An environment is turbulent, dynamic, etc., if the mapping from firm actions to performance outcomes changes frequently, profoundly, and in ways that are difficult to predict."* Although we completely agree with specifying environmental change in terms of its frequency and scope, we find the notion of predictability problematic. As it bears a close connection to environmental complexity, for a discussion of this aspect, we first have to clarify the meaning of complexity.

Complexity of the organizational environment significantly impacts the comprehensibility of work conducted in an organization (Mintzberg, 1979:273-281). Therefore an important aspect that surfaces in almost all environment frameworks with relation to complexity is the diversity of environmental elements. For example, complexity arising from product diversity (Thompson, 1967) implies that the organization needs to understand a broader range of products and a broader resource space (Haunschild & Sullivan, 2002:618).[63]

Besides the sheer number of environmental elements, the comprehensibility of work is also affected by the elements' interdependence (Lawrence, 1981). In a complex environment, the organization needs a higher degree of sophisticated knowledge to cope with its surroundings (Sharfman & Dean, 1991:685). A complex task is therefore not merely characterized by the necessity to deal with a large number of different elements but also to take into account their interactions. Simon (1962) gives a specification of a complex system which still shapes the notion of complexity today (Nickerson & Zenger, 2004:601). A complex system is *"made up of a large number of parts that interact in a nonsimple way"* (Simon, 1962:648).

With this definition of complexity we return to the different aspects which characterize environmental change. Similar to Suarez & Oliva (2005:1022), we exclude the notion of predictability from a framework of environmental change for three reasons: First, we consider predictability to vary with the pattern of frequency and scope of change; frequent and large alterations make environments more difficult to predict. Second, complexity which we model as a separate feature of the environment is also likely to interfere with predictability. The number of environmental dimensions and their level of interactions can be expected to have an impact on predictability. Third, modeling predictability most likely involves

63 Variety, therefore, impacts the capacity of a system to adjust (Ashby, 1956:126). Interestingly, Ashby (1956) related the internal variety of a system to the variety present in the environment. In his law of requisite variety, he states that *"only variety can destroy variety"* (Ashby, 1956:207). To keep organizational performance in the presence of environmental variety, the organization needs to maintain a certain level of internal variety. With relation to organizational learning and knowledge, this is also echoed by Cohen & Levinthal's (1990:129-130) notion of absorptive capacity. To assimilate new or changed knowledge, the organization requires related knowledge in its knowledge pool. Heterogeneity of knowledge inside the organization, thus, is deemed to be a prerequisite of adaptability and flexibility. We will discuss this aspect in more detail with relation to our model in chapter 4.1.

subjective perceptions, but we aim at finding representations of objective criteria for environmental change.

Building on the foregoing discussion, we define environmental complexity and turbulence as being composed of the following aspects:

Environmental complexity	Number of environmental dimensions
	Interdependence of environmental dimensions
Environmental turbulence	Frequency of environmental change
	Scope of environmental change

Table 3: Categorization of the organizational environment

To account for the effects of the environment on the unfolding of path-dependent learning, we further specify different scenarios of complexity and turbulence. In the case of turbulence, these scenarios are combinations of the frequency and scope of change. Here, we use a typology which leans towards the specification of environmental change of Suarez & Oliva (2005:1022-1023). Still, as our configuration of the environmental variables is not completely congruent with their approach, the different types of environmental change cannot be entirely compared.[64] In the case of environmental complexity, we basically distinguish between three different levels.[65]

[64] Suarez & Oliva (2005:1022) base their typology on four different attributes characterizing environmental change. Besides frequency and scope their typology involves the speed and amplitude of change.

[65] In chapter 5, we explain why we focus on the variation of the interdependence of dimensions to account for the different regimes.

Regimes of environmental complexity	Simple environment	Moderately complex environment	Highly complex environment

Regimes of environmental turbulence	Low frequency of change	High frequency of change
Low scope of change	Regular regime	Gradual regime
High scope of change	Disruptive regime	Hyper-turbulent regime

Table 4: Scenarios of environmental complexity and turbulence
(Regimes of turbulence adapted from Suarez & Oliva, 2005:1022)

A thorough investigation into the contextual effects on path-dependent learning has to account for differing regimes of complexity as well as for various combinations of the scope and frequency of environmental change. This requirement also plays an important role in the choice of our methodological approach in chapter 3.

2.4 Summary and Outlook

So, where does the foregoing discussion leave us? Chapter 2 encompassed three important steps towards an analysis of the role of the environmental context for organizational path dependence. After introducing the theory of path dependence, its central characteristics and process steps, we first showed that analyses of path dependence so far have neglected the influence of the environmental context. Even if some pointed out that it has to be considered an important factor for the unfolding of path dependence, the effects of differing contexts have mostly not been dealt with which is especially true for organizational path dependence.

Second, we have pointed out that the relevant mechanism to consider for an analysis of the influence of the context are learning effects since organizations connect to their environments in processes of learning. With regard to learning effects, we demonstrated that these are underdeveloped in organizational path dependence theory leaving open the mechanism's exact functioning with respect to its elements and interacting processes.

Third, we proceeded into the literature on organizational learning to develop a theoretical framework which details the learning mechanism in organizational path dependence. We started out with a definition of organizational learning comprising the concepts of experience and knowledge. Organizational learning here emerged to be a multifaceted concept involving different repositories and domains. We emphasized that the involvement of different learning levels in organizations is what mainly constitutes this multifaceted nature and where most of the differing viewpoints on organizational learning stem from. We outlined that in contrast to other mechanisms leading to path dependence like coordination or complementarity effects, learning effects are special. Their qualities for adaptation cannot be separated from their rigidifying tendencies. Thus, it is an imbalance in learning which leads to path dependence which is often described as exploitation crowding out exploration. To identify the elements and processes at work in path-dependent learning, we dealt with this crowding out dynamic as an interaction process between different levels in the organization and further in terms of the involved variation and selection processes.

We incorporated our findings in a theoretical framework of path-dependent learning which specifies the learning processes at the different levels as well as how the organization connects to its environment. We finished chapter 2 by identifying complexity and turbulence as the most important descriptors of organizational environments and further stressed their significance for our research by arguing that subsequent analyses in path dependence have already hinted at their relevance. Based on the definition of the two environmental attributes we defined environmental complexity, and the frequency and scope of environmental change as key variables in our research. In accordance with our framework these independent variables are supplemented by variables which define the settings inside the organization in which the learning takes place. In chapter 4.1.3, we shall clarify a sufficient way to incorporate the internal settings without losing our primary focus on the organizational environment.

Independent variables	Dependent variables
Complexity of environment	Learning success at org. level
Frequency of env. change	Learning success at ind.level
Scope of env. Change	Knowledge heterogeneity
Settings of the learning processes inside the organization	

Table 5: Overview of independent and dependent variables[66]

Our dependent variables focus on identifying path dependence in organizational learning. Concluding from the identification of the different levels involved in organizational learning and the inefficiency criterion of path dependence theory, a diagnosis of path dependence must be based on assessing the learning success at the individual and the organizational level. Since the learning ability of the organization is closely connected to the knowledge variety in the organization, it is the heterogeneity of knowledge in the organization which offers conclusion concerning the rigidity of the organization.

Chapter 2 dealt with the theoretical preliminaries. Here, we identified the gap in path dependence theory and provided a theoretical framework. The theoretical framework clarified the processes and elements involved in the path-dependent learning mechanism and, consequently, is a necessary basis for the subsequent steps. In chapter 3 and 4, we shall continue by explaining the means by which we can tackle our research focus. For this purpose, two steps are necessary. First, in chapter 3 we delineate our methodological approach and outline the advantages of the computational method for path dependence research. Second, in chapter 4, we discuss how existing computational models relate to our research focus and deal with their dynamics with regard to organizational path dependence. To approach the computational models, we use a central distinction which emerged in our theoretical framework. Here, we identified two feedback loops, one involving the individual level

[66] The set of variables especially with respect to the settings of the learning process inside the organization will be further detailed in chapter 4. For the complete overview see 4.3. The colors used to highlight the variables which specify the organizational settings indicate if they relate to learning at the individual level (green) or organizational level (orange). For a better orientation, variables of the environmental context throughout are highlighted in blue, dependent variables in yellow.

and the other connecting the individual and the organizational level to be at the heart of path dependence in learning. Based on the two feedback loops, we identify which models provide a useful approach to tackle either individual learning or learning involving the organizational level. For both model types we work out the central dynamic and detail its path-dependent nature. Based on this, we discuss how far research conducted with the different models can take us with regard to our research question. Here, we argue that only an integration of both dynamics in one model is able to represent the path-dependent learning mechanism. We conclude by speculating how the different dynamics will unfold in interaction and under the influence of environmental complexity and turbulence.

In chapter 5, we outline our computational model and describe its elements, processes and transform the variables into model parameters. Subsequently, in chapter 6 we conduct experiments with the model and inquire into its behavior in varying environments. After anchoring the model in existing research by reproducing already achieved results, the two experimental chapters therefore aim at answering the following questions:

> How does environmental complexity influence path-dependent organizational learning?

> How does environmental turbulence influence path-dependent organizational learning?

Our interpretation of the experimental results in the final chapters again strongly alludes to the two dynamics in the model.

3 METHODOLOGICAL APPROACH

In the preceding chapter, we specified self-reinforcing organizational learning as consisting of interacting processes which are embedded in an organizational context. These non-trivial processes connect an organization to its environment which itself is characterized by differing degrees of complexity and turbulence. In understanding phenomena which result from multiple interdependent processes, traditional research approaches are most likely of limited use (Harrison et al., 2007:1229). In the following section, we outline why computational modeling is of special relevance for path dependence research by building on the characteristics of path-dependent processes. We continue by giving a brief introduction to computational modeling in which we define it in the context of the social sciences, clarify the benefits and limitations arising from a central characteristic of computational modeling and show its significance for theory building. Based on the foregoing explanations, we specify our simulation approach and consider the suitability of NK landscape models for our research focus. We finish the methodological chapter by pointing out the steps involved in computational research as these guide our inquiry in the following chapters.

3.1 The Relevance of Computational Modeling for Path Dependence Research

We already pointed out that path dependence is not merely a concept for referring to historical sequences, by which it would lose most of its theoretical significance, but that it goes far beyond this general approach (Sydow, Schreyögg, & Koch, 2009). Path-dependent processes are characterized by a self-reinforcing logic, and it is this dynamic which endows them with many of their specific properties. Vergne & Durand (2010:737) argue that these properties are responsible for *“the missing link between theory and empirics of path dependence.”* The gap between theory and empirics results from the fact that specific properties of path dependence cannot be demonstrated in empirical research. Case studies of path dependence[67] always involve thought experiments concerning the outcome of the process if history had taken a different turn and as such are reproached with suffering from many problems such as incomplete data, opaque contexts and cognitive biases of the researchers.[68] This results in a major problem for the credibility of path dependence research.[69] To counteract this impasse, Vergne & Durand (2010:737) recommend making use of highly controlled research methodologies such as laboratory experiments or computer simulations. Lab experiments and computer simulations have many similarities. Carley (2001:69), for example, considers simulations to be virtual experiments. Lab experiments therefore exhibit similar qualities for inquiries into path dependence (Vergne & Durand, 2010:750). Still, lab experiments cannot be considered useful or even feasible on all levels of analysis in path dependence research.[70] As can be seen from Bach (2008), Koch, Eisend, & Petermann (2009) and Langer (2011), they mostly focus on the individual level. Inquiring into the complex interaction of levels involved in path-dependent organizational learning is surely difficult or even impossible through lab experiments. Not only, is it extremely complicated to replicate the organizational setting and handle the flows of information in an experiment (Egidi & Narduzzo, 1997:679), the evolutionary nature of the process under differing conditions is hard to capture. As Lant & Mezias (1990:151) put it: *"It is difficult to explicate how the processes unfold over time in different contexts to yield various organizational outcomes."* They argue that for research foci of this kind a computer simulation is the appropriate means for reaching conclusions. In the following, we elaborate how the characteristics of path-dependent processes connect to simulation research.

1.) Path-dependent processes are non-linear processes due to the workings of self-reinforcing mechanisms. This property can also be described as sensitivity to initial conditions or the 'small cause, large effect principle'. Very small

[67] Prominent cases are the QWERTY study (David, 1985) described in chapter 2.1.1 or the competition between the video formats VHS and Beta (Arthur, 1990).

[68] See on these limitations also Mahoney (2000:537) and Koch, Eisend, Petermann (2009:68). Vergne & Durand (2010:751) claim that case study research can benefit from stringent counterfactual analysis. On the benefits and limitations of counterfactual analyses see also Durand & Vaara, (2009).

[69] This problem is also reflected in the effective critique of Liebowitz & Margolis (1990) in which they question the relevance of path dependence for example by referring to gaps in the evidence of the QWERTY case study (David, 1985).

[70] Sydow, Schreyögg, & Koch (2009:705) in this respect differentiate between individual, organizational, network, and field level.

differences at the beginning of a process, as for example in the history of the agents' activities, can lead to rapidly diverging paths of system behavior (Simon, 1998:461; Carley, 2001:77). Nonlinearity is commonly obtained through positive feedback that reinforces the initial change (De Wolf & Holvoet, 2005:12). It is often impossible to understand nonlinear systems analytically as there is no set of equations which can be solved to forecast how the system will develop (Gilbert & Troitzsch, 2005:10). As conventional statistical models almost all assume a linear relationship between variables: these are not suitable either. To increase our knowledge about nonlinear systems, their processes have to be studied repeatedly under very similar conditions to discover when critical junctures may arise, but generally social scientists observe only one historical path (Castaldi & Dosi: 2004:19). Therefore the only commonly effective way to study nonlinear systems is in terms of computer simulations. Here the researcher is able to repeat the history of a process under varying conditions, which does not assume away the general unpredictability of nonlinear processes but at least creates knowledge how it works (Gilbert & Troitzsch, 2005:10).

2.) Another important property of path-dependent processes, their contingency, cannot be confirmed in case study research either. Whereas contingency is often equated with randomness of events (Vergne & Durand, 2010:745), the theory of organizational path dependence considers the contingency which characterizes the first stage of path development as being imprinted by the organization's past. The initial events are therefore not completely random but are often too specific to be captured by existing scientific explanations. Even so, the chance character of these events is difficult to prove in empirical path dependence research. Here, it is always possible to attribute the pattern of events, for example the adoption decisions in the case of the competing video formats VHS and Betamax, to causes which have been overlooked in empirical research. As these causes, for example some product characteristic which made VHS more attractive to the customer than Betamax, can never be totally excluded, the contingency of path-dependent processes in empirical research cannot be verified (Vergne & Durand, 2010:745-746). In simulation studies, the claim of contingency holds as alternative causes for the unfolding of events are by definition excluded.

3.) In path dependence research we analyze complex systems which consist of many parts, in the case of social systems, usually individuals which interact (Carley, 2001:77). These interactions as mechanisms of internal change and adaptation give rise to the properties of self-organization and emergence. The concept of emergence defines a novel property, structure, or behavior that arises on the macro level of a system as a result of the interactions on the micro-level. Self-organization, in contrast, refers to an organizing process which happens without external control, a dynamical and adaptive increase in order without a central authority or planning (De Wolf & Holvoet, 2005:9-11).[71] In most complex systems emergence and self-organization occur together. In path dependence theory, we experience an emergent behavior on the macro level, the organizational path, which is based on specific self-organizing behavior on the individual level. Isolating the dynamics at the micro level which result in emergent behavior at the macro level and again proving that the behavior at the macro level is truly emergent is a daunting task in empirical research but one of the major strengths of simulation research.

4.) The property to which most of the critique of path dependence research is related is the inefficiency of path-dependent outcomes.[72] Two of its aspects have to be considered here, one relating to the identification of inefficiency, the other to the implied time frame of the lock-in (Vergne & Durand, 2010:747-748). First, suboptimality of seemingly path-dependent results is difficult to prove as it is connected to the perspective taken. In Arthur's model (1989), inefficiency was defined as agents experiencing regret but from the perspective of the company selling the winning technology it is surely an efficient state. Claims that our reality is suboptimal, therefore, can only be made with reference to a specific audience. But even then proving that we live

[71] Emergence and self-organization are often used as synonyms but actually they have a complementary relationship. They differ mainly with respect to two properties. Novelty of the emergent behavior, (the behavior must not be known on the micro level of the system) and the micro-macro link are necessary for emergence but not for self-organization (De Wolf & Holvoet, 2005:9-11).

[72] See Liebowitz & Margolis (1990; 1995).

in a suboptimal world can necessarily only be based on comparing current situations with different scenarios which might have been possible (Vergne & Durand, 2010:747-748). That such a claim is difficult to uphold, comes as no surprise. The second aspect pertains to the time frame of suboptimal states. With a sufficiently long time frame most lock-in situations can be assumed away. It could be argued, for example, that the market had not locked into VHS as today everybody uses DVD or Blu-ray (Vergne & Durand, 2010:747-748). In the long run, these path-independent explanations are probably true.[73] Related to the argumentation in neoclassical equilibrium theory, long run explanations can be held against path dependence research and cloud its relevance.

We conclude that all these general properties of path-dependent processes strongly point to a simulation approach. Computer simulations are explicitly well-suited for analyzing processes of a non-linear character. With respect to contingency and inefficiency, simulations are computational laboratories in which the researcher can repeat an experiment for the same initial conditions and parameters and thus prove the contingency of a process, as well as determine the existence of possibly superior outcomes to account for the inefficiency of a path-dependent result. Generally, in modeling the system of interest, the researcher defines a consistent model which focuses the research process and its results on the specified constructs and model logic, and, thus, immunizes the results from alternative explanations.[74]

Before we specify our simulation approach in more detail, we give a brief introduction to computational modeling. In this introduction, we present a definition, delineate computational modeling as a method aiming at theory building and describe both its benefits and limitations.

73 A popular critique of long run explanations which assume away problematic situations in economics was brought forth by J. M. Keynes (1928:80): *"The long run is a misleading guide to current affairs. In the long run we are all dead."*

74 Computer simulations therefore are especially useful for contributing to research which is not limited to establishing co-variation between two variables but which aims at specifying the mechanism behind a connection of variables. As mechanisms always are theoretical constructs of which only the effects can be observed (Hedström & Swedberg, 1996:290), simulations can be used to model mechanisms and to observe if these produce the effects noticed in reality.

3.2 Brief Introduction to Computational Modeling

Harrison et al. (2007:1231-1232) claim that simulation methodology, compared to empirical or analytical approaches, is still seldom used in management theory. While Davis, Eisenhardt, & Bingham (2007:480-481) make out a recent increase in publications using simulation methodology, they also recognize that its value for theory development still remains controversial. The authors ascribe the limited dissemination of simulation methodology and the controversy concerning its value to a lack of clarity about the method. It is therefore the purpose of this chapter to define computational modeling, clarify its benefits and limitations and outline how simulation research can contribute to building and extending path dependence theory.

3.2.1 Defining Computational Modeling in the Social Sciences

In general, in computational modeling, the researcher describes a model within a set of computer code (Carley, 2009:47). A computer or a network of computers runs this code iteratively based on the configuration of the initial and boundary conditions, thus generating results for the system's dynamic behavior. The simulation creates a detailed time path for the system, in this way enabling the researcher to follow the system's results in each time step (Simon, 1998:459). This implies that, similar to statistical models, simulations have input variables, which are used to configure the simulation for a specific setting, and output variables which are derived from the behavior of the model (Gilbert & Troitzsch, 2005:2). Although computer simulation must be differentiated from deductive and inductive forms of science, it encompasses aspects of both (Harrison et al. 2007:1230). Axelrod (1997:3-4) therefore referred to computer simulation as a third way of doing science. We come back to this peculiarity in the following chapter in which we deal with theory building by means of computer simulations.

Computer simulations have been applied in different domains and by different communities of interest (Axelrod, 2006:1567; Goldsman, Nance, & Wilson, 2009:310). This breadth in disciplines, as physics, meteorology, sociology, psychology, and economics as well as the different types of models at first glance cause confusion (Meyer & Heine, 2009:496). Interestingly, if one looks closely at the different areas of research one notices that often the problems which have been tackled with simulation methods, are quite similar. Simulations are always used to gain a better understanding of complex systems. Thus, we often find astonishing parallels between different disciplines when comparing their simulation approaches to certain problems. For example, in the first edition of the Journal of Artificial Societies and Social Simulation the three published articles came from as distinct scientific domains such as anthropology, economics, and computer science, but they all involved general issues of the social sciences, the role of culture, modeling institutions and ideology. Simulations, therefore, often support the integration of findings from different areas of research. In this way, reasoning about dynamic systems in terms of computational models helped complexity theory to evolve as a means to rethink and extend social theories (Carley, 2001:77).

The tremendous value of computer simulations with respect to analyzing complex systems (Carley, 2001:77) allowing the researcher to sidestep the limitations of the empirical approach seems to be the main reason why nowadays simulation research has gradually become more accepted in the social sciences.[75] Despite a quite strong start, which was pioneered by James March and colleagues (Cyert & March, 1963; Lave & March, 1993), in the 1970s and 1980s, simulation methodology then drifted into the periphery of organization science (March, 2001:xi-xiv).[76] Different reasons can be identified which made results achieved with computer simulations difficult to access for the social science community. Simulation modeling involves a high level of abstraction which used to be rather uncommon in the social sciences, and simulation as a method was mostly neglected in social science curricula (Harrison et al., 2007:1231). But most importantly, early work in simulation research did not match social science research in another respect. Instead of being focused on understanding and explanation as common in social science research, the specific simulation approaches used in the early days of computer simulation, as discrete event

[75] For the development of social simulation in an analysis of citation and co-citation see Meyer, Lorscheid, & Troitzsch (2009).

[76] March (2001) claims that simulation methodology in the social sciences mainly survived because it was practiced in places shielded from disciplinary orthodoxy. *"In that sense, simulation modeling survived by recruiting the alienated and the marginal"* March (2001:xiv). Often simulation research connected itself more to the community of computing and thus did not threaten dominant groups or methodologies in central areas of the social sciences.

simulations or system dynamics, were more concerned with forecasting (Gilbert & Troitzsch, 2005:8). This research purpose alienated simulation methodology from social science research almost leading to a complete breakdown of social simulation. Due to the development of multi-agent models, in the 1990s this changed. Multi-agent models as a bottom-up approach offer the possibility to simulate the interaction between autonomous individuals and the emergent results. They thus account for the described strong position of computer simulation in understanding nonlinear dynamics.

However, in organization theory, simulation research seems to have made less impact than in other social science areas such as economics or psychology (Harrison et al., 2007:1232). Recently we can identify an increasing number of publications which point to the development of a new community in organization theory concerned with simulating organizational processes. Often their work is rooted in the behavioral theory of the firm and builds on the results of James March and colleagues but also integrates new insights from complexity theory. For designing our path-dependent model of organizational learning, we build on the research results of this community.[77]

In the social sciences, researchers using computer simulations are often criticized based on one specific feature which is essential for this research methodology: Computer simulations always involve a rather high level of abstraction. In the following chapter, we therefore connect the simplification involved in building computational models to the benefits and limitations of this methodology.

3.2.2 The Beauty of Simple Models: Benefits and Limitations of Computer Simulations

Having clarified the suitability of computational modeling for path dependence research, this chapter aims at providing a clearer picture what we can expect from tackling our phenomenon of interest with a simulation approach. We find that most of the benefits and limitations of computational modeling relate to simplifying complex phenomena.

[77] See chapter 4 which provides an assessment of the different models encompassing dynamics of individual or organizational level learning.

Like a map, every model, unavoidably, is a simplified version of the target which is modeled (Gilbert & Troitzsch, 2005:19). It is most of all the simplification of the modeled system which gives us a clearer picture of the dynamics at work. A model which replicates the full complexity of the modeled target would be as useless as a map which incorporates every aspect of a real landscape. Orientation would get lost in detail (Michalewicz & Fogel, 2004:16). Thus, the beauty of most models lies in their reduced complexity, in providing a glimpse at the underlying dynamics which cause the effects that are observed in real life.[78] Goldstein & Gigerenzer (2011) argue in favor of simple models:

> *"Simple models, from physics to psychology, have driven much of progress in science. Yet no model, simple or complex, can explain all behavior. The beauty of simple models is that one can easily discover their limits, that is, their boundary conditions, which in turn fosters clarity and progress."* (Goldstein & Gigerenzer, 2011:392)

Simple models themselves are thus often limited to demonstrating the workings of well-defined processes but often their results are applicable to a rather broad range of observable phenomena (March, 2008:293).[79] Epstein (2008) points out another important aspect:

> *"Simple models can be invaluable without being "right" in an engineering sense. Indeed, by such lights, all the best models are wrong. But they are fruitfully wrong. They are illuminating abstractions."* Epstein (2008:1.1.2)

Accordingly, the beauty of simulation models rises and falls with respect to the most important question in designing a model: The researcher has to decide what can be omitted from the model and what must be included. Beauty lies in transparency with respect to model complexity and model comprehension but it should not lure the researcher to stray too far from realistic assumptions. A good example where the quest for model beauty had a detrimental effect is the equilibrium model in economics.[80]

78 This relates closely to the benefits of mechanism explanations as described by Hedström & Swedberg (1996).

79 A good example is the model of mutual learning in a social network that changes as a result of learning. The model can be applied to diverse processes of institutional integration, for example European integration (March, 2008:285).

80 In economics, equilibria with a pareto-optimal allocation of resources only develop under a set of very restrictive assumptions, e.g. perfect rationality of the market participants (Simon 2000:244-245).

But there is also a great temptation to incorporate too much detail into a model. The more parameters are integrated, the more conclusions can be clouded by assumptions made on the side of the parameters or by interactions between the parameters (Gilbert & Troitzsch, 2005:19-20). A good model evolves in the tension between simplicity and elaboration (Harrison et al., 2007:1240) and how this tension is solved must be closely connected to the research purpose.[81]

This argumentation can be extended to touch upon two crucial aspects of research, internal and external validity. The computational rigor which is involved in model building consisting of selecting, operationalizing and linking the constructs contributes to internal validity. In designing simulation models, the researcher has to unequivocally define the theoretical logic of the model and to make explicit its boundary conditions. The underlying theory and its scope with relation to explicable phenomena often becomes much more obvious than in empirical research. External validity of simulation research, on the other hand, can be weak as simulation reduces complexity to get a clearer picture of phenomena in the real world (Davis, Eisenhardt, & Bingham, 2007:495). Here again, it is the task of the researcher to balance the purpose of his research with the required elaboration or simplification of the model (Harrison et al. 2007:1241).

Another strength of simulation research at least partially mitigates this weakness. As Axelrod (1997:4) argues, simulation can be considered as conducting thought experiments. With a simulation model, the researcher creates a computational laboratory in which experiments over large parameter spaces can be carried out. This does not do away with the necessity to select the adequate model components and correctly specify their linking logic but the extremely large variations in and the high number of experiments which can be conducted in computer simulations, especially when compared to laboratory experiments, ease restrictions for the researcher in terms of prior determination of parameters. Simulations endow the researcher with the possibility to relax assumptions, unpack constructs and add new features to test their effects on the research question (Davis, Eisenhardt, & Bingham, 2007:495-496).

To deal with the aforementioned dangers and limitations, the researcher is urged to obey the KISS principle in which Axelrod (1997:4-6) suggests keeping it simple and

[81] We deal with this in more detail in the subsequent chapter.

stupid. Starting with a simple representation which can be easily checked for correctness, the researcher should then employ the building block method for elaborating the model in a stepwise fashion (Harrison et al., 2007:1241). We follow this proposition in our experimental chapter[82] and increase the complexity of our model step by step. In this way, it is possible to examine the consequences of the added complexity and to strike a balance between elaboration and simplicity.

The level of simplification or abstraction of a model also influences what it is able to explain. The following chapter deals with three different purposes of simulations and relates these to their capacity to build or extend theory. Based on these explanations, we specify the aim of our simulation.

3.2.3 Theory Building with Computer Simulations

Doing simulation research involves inductive and deductive reasoning. When using computer simulations, we build on a set of explicit assumptions about constructs and processes which specify our modeled system. However, we are not concerned with proving a theorem, but instead our model generates simulated data for system behavior under various conditions. This data is then analyzed inductively. Because of the non-linearity of the system which may result in emergent macro effects, the results even of simple assumptions concerning the constructs and logic of the model are not at all obvious (Axelrod, 1997:4). As computer simulations release us from the constrictions of theorem proving, or, in other words, of constructing a model which is analytically solvable, we are not constrained with regard to the underlying assumptions. Usually in analytical reasoning, assumptions of the model have to be adapted in a way to make the model solvable. Analytical models often aim at finding out the equilibria or end state of a process while simulation models have their focus on the processes which lead to them (Baumann, 2008:49). It is also important to notice that computer simulation cannot be considered as a simple linear process which moves from a deductive to an inductive stage. Rather, it requires iterating between deductive

[82] See chapter 6.

and inductive reasoning when building a model and conducting experiments (Gilbert & Troitzsch, 2005:26).[83]

Even if in computer models real world phenomena have to be simplified, a social scientist when designing a computer model will realize that there is a gap between what is specified by verbal theory and what is needed to design a computer model. Moving from a verbal to a formal theoretical representation generally requires the researcher to inquire more deeply into the underlying assumptions and relations which often are only implied in verbal theory (Carley, 2001:71). Epstein (2008:1.2-1.4) in this context claims that everybody is a modeler. Every researcher in his head runs some kind of model when trying to figure out how a specific dynamic works. These models are commonly implicit; they often have hidden assumptions, untested internal consistency and logical consequences. In contrast, computer simulations are explicit models. Independent from the various purposes of simulation models, with which we deal in the next paragraph, one of their most substantial contributions to theory building consists in making every assumption, construct, process and how they are linked to each other obvious. By generating data for a large range of possible scenarios, their internal consistency and logical consequences can be tested (Epstein, 2008:1.3-1.5).

Different computer simulations have different purposes. A very general distinction which is made in most simulation literature differentiates between simulation models which aim at prediction and others which focus more on explanation (Carley, 2001:69-70; Simon, 1998:458; Gilbert & Troitzsch, 2005:4-5; Heath, Hill, & Ciarallo, 2009:2.16-2.18). These two purposes of simulation are not mutually exclusive but rather should be understood as the two ends of continuum. The researcher's knowledge about the system of interest determines where on this continuum a simulation is located with respect to its research purpose (Heath, Hill, & Ciarallo, 2009:2.16).

[83] We will deal with this aspect in more detail when outlining the steps in simulation research in chapter 3.4.

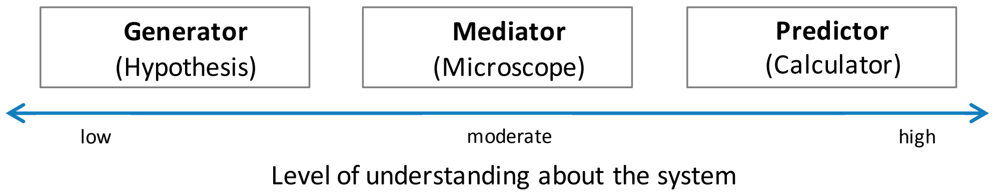

Figure 5: **Purposes of computer simulations**
(Source: Heath, Hill, & Ciarallo, 2009:2.16)

Prediction can only be achieved if the researcher deals with a system where the level of understanding is very high. Often these systems are less complex, as in the case of simple queuing systems or well defined and understood production systems. At the other end of the continuum, if little is known about the system, the simulation serves as a generator of hypotheses. If researchers do not know which processes bring about a certain behavior, simulations serving as generators can test if a specific conceptual model is able to explain an observed behavior. With moderate knowledge about the system, simulations typically have a mediator role. Although not a complete representation of the system, these simulations help to ascertain that the conceptual model can represent the system and then to further inquire into its special features and behavior (Heath, Hill, & Ciarallo, 2009:2.17-2.18), for example, to illustrate which results are achieved under specific conditions (Harrison et al. 2007:1239).

In our case, the simulation has a mediator role. We specified what we consider to be the learning processes involved in the crowding out dynamic in organizations. As a representation of the self-reinforcing learning mechanism, other effects at work in organizations, such as complementarity or coordination effects (Sydow, Schreyögg, & Koch, 2009:700), are not integrated. Since we do not aim at giving a full representation of the organizational system, simulating our theoretical framework does not aim at predicting. We are aware that the dynamics observed in our model in reality must be confounded by other effects which interact with the learning processes.[84] We deliberately isolate the dynamic of learning effects to gain a better insight into its path-dependent qualities under different contextual conditions. Our simulation model therefore does not aim at generating new theory but, for the specified processes,

[84] Brenner (2006:928) in this regard argues that due to the various settings in which learning takes place, the different types of knowledge, and the different levels involved, there exists no universal model of organizational learning. A learning model consequently has to be narrowed down to represent the phenomena which are the focus of the researcher.

focuses on testing the theory of path dependence and on giving theoretical implications as to the integration of the environmental context.

The computational method involves a variety of different approaches. The purpose of the model, its level of abstraction as well as the characteristics of the modeled phenomenon determine which simulation approach is suitable. In the following chapter, we proceed by considering the usefulness of different approaches for our research.

3.3 Specifying the Simulation Approach: NK Landscapes

We have outlined above that simulation is a useful way to tackle questions in path dependence research. In this chapter we take the next step and specify the simulation approach. In the literature, we find different typologies for simulation modeling (Gilbert & Troitzsch, 2005; Davis, Eisenhardt, & Bingham, 2007; Harrison et al., 2007). Davis, Eisenhardt, & Bingham (2007:485) point out that the choice of the simulation approach is extremely important since every approach involves its own theoretical logic and assumptions. They even equate the choice of a simulation approach with the decision for a theoretical framework as it specifies the means by which the research problem is analyzed.

Three commonly used simulation approaches are system dynamics, cellular automata, and multi-agent models (Harrison et al., 2007:1237). Comparing the three approaches, a very general distinction between simulation approaches becomes obvious. Simulation approaches either model systems as an undivided whole or as being composed of different entities or agents for which the adequate behavior is specified. In system dynamics, in this respect, the system is described as a set of differential equations which describe how the system changes over time. As such, system dynamic models display how different variables affect each other (Gilbert & Troitzsch, 2005:29-30; Harrison et al. 2007:1237-1238).[85] In the other category of simulation approaches fall both agent based models and cellular automata. In these simulation types, the system behavior develops from the behavior of the multitude of agents

[85] For examples of system dynamic models in management and organization theory see Perlow, Okhuysen, & Repenning (2002), Repenning (2002) and Repenning & Sterman (2002).

modeled. These simulations thus do not specify the behavior of the system as an entity in itself but they deal with the behavior of its components and observe the results of their interaction. System behavior here is an emergent property (Gilbert & Troitzsch, 2005:130-171; Macy & Willer, 2002:147-148; Harrison et al. 2007:1237-1238). As for our model, the emphasis lies on interacting agents from which the system behavior results. Clearly these specifications rule out simulation approaches from the field of system dynamics and point to the simulation types which accentuate the micro level.

Concerning the emphasis of the micro level, cellular automata are similar to agent-based approaches but the agents here are represented by the cells on a uniform grid. Although cellular automata are able to feature emergence resulting from the behavior on the micro level, the focus of this approach is on patterns which arise from spatial processes as for example diffusion processes (Davis, Eisenhardt, & Bingham, 2007:486).[86] For our research focus the spatial distribution of the agents[87] can be considered irrelevant because we stress the individual learning dynamic and the interaction between individual and organizational level.

Compared to other simulation types, agent-based approaches are distinct in their aim to feature agents which interact with their environment in an intelligent way. The word 'agent' points to a concept which ranks first in these models, the concept of agency. Two criteria in our case point to an agent-based approach: First, in our theoretical framework,[88] the individuals are highly significant for the learning process and second, organizational learning is supposed to align organization and environment. In multi-agent models, agents are little computer programs which incorporate many aspects of human activity and its intentional nature. They have the ability to perceive their environment and base their actions on their knowledge of it. Moreover, they are socially capable of interacting with other agents (Gilbert & Troitzsch, 2005:172-198). Models of organizational learning, therefore typically are agent-based approaches.[89]

[86] For an example of cellular automata models in management and organization theory see Lomi & Larsen (1996).

[87] See Miller, Zhao, & Calantone (2006) for a learning model in which the agents are situated on a grid and local interactions are assumed.

[88] See chapter 2.2.5.

[89] We deal with relevant models in organizational learning in chapter 4.

Multi-agent approaches can also be divided according to type.[90] For further narrowing down our simulation approach, the environment in which the agents are placed is crucial. The specification of the environment in agent-based approaches depends on the system which the researcher intends to model; for example, it can represent a special context, a network, or a specific problem structure. We described in our theoretical framework the environmental characteristics which we consider important for the unfolding of path-dependent learning. Describing the organizational environment in terms of its attributes, in our case complexity and turbulence, involves dealing with a highly abstract representation of the environment. Abstract representations of the environment usually consider the environment to be composed of an m-dimensional vector which the individual learners have to figure out. The environment in this case is represented as a set of m elements which can have different states described in terms of the element's values, for example −1 and 1 (March, 1991; Miller, Zhao, & Calantone, 2006; Kim & Rhee, 2009). These values do not capture any positive or negative rating of the concerned environmental dimensions; they are simply conditions which the organization aims to find out.[91]

Although bearing some resemblance to this abstract environmental representation, the NK landscapes approach significantly enriches this concept. Based on information about the background of the NK approach, in the following we outline the characteristics which make NK models particularly relevant for research inquiring into path dependence and its relation to the organizational environment.

The NK approach has its roots in biology (Kauffman, 1993; 1995)[92] and was first adopted for organization theory by Levinthal (1997).[93] Generally speaking, an NK

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90 See the overview of simulation approaches in the organization and strategy literature in Davis, Eisenhardt, & Bingham (2007:486). With relation to agent based approaches they mention cellular automata, genetic algorithms, NK landscapes, and stochastic processes.

91 This implies the assumption that a correct representation of reality implicates learning success as it helps the organization to adapt its behavior to external requirements, see on the characterization of the organizational environment also chapter 2.2.5.

92 See on the transferability of simulation approaches to other domains chapter 3.1.

93 In his model, Levinthal (1997) uses the interactions which can be modeled by the NK approach to exemplify the complexity of organizational attributes. As a result, his model describes the organizational level of adaptation; the agents in his simulation are not individuals but whole organization trying to find the best combination of attributes. This application can be found quite often in organization theory; the NK landscape symbolizes the complexity of the decisions of organizations concerning for example organizational form, product design, and organization strategy (Ganco & Hoetker, 2008:3).

landscape is a mathematical representation of a complex system consisting of a large number of parts which interact.[94] The relation between the landscape and the agents is that of a complex problem and the entities that search for its best solution. The search dynamics in the NK approach is often referred to as walk of the agents through a landscape. Consequently, in many explanations of the NK methodology, in a simplified way such a landscape can be visualized like a real landscape which involves higher and lower peaks (Michalewicz & Fogel, 2004:42; Rivkin & Siggelkow, 2006).[95] The local optima in the landscape result from the interaction of the landscape's dimensions. Increasing problem complexity as an increase in the interaction of dimensions therefore yields a higher number of local optima and makes identifying the best solution more challenging for the agents. The notion of NK refers to this scalable complexity. While N defines the number of elements a problem landscape consists of, K specifies with how many other elements each single element interacts.[96]

94 This specification is consistent with the definition of a complex system given by Simon (1962:648).

95 Kauffman & Levin (1987:27) already used the 'Alps metaphor'. They explain the correlation between two neighboring points in the NK landscape by comparing it with the correlated altitude of two close spots in a mountainous region. *"If one moves horizontally 1 metre, the altitude of the point at which one lands is, even in the Alps, highly correlated with the altitude of the initial point. If one moves horizontally for 50 kilometres, the altitude is essentially uncorrelated."* In learning models, two neighboring points in NK can thus be considered to be closely correlated concerning the state, they represent. Jumping in the landscape in this case implies acquiring large amounts of knowledge uncorrelated to the current knowledge which in learning can be considered rather unlikely.

96 In its original application in biology, N in the NK framework refers to the number of alleles in the genome and K defines the density of epistatic connections. Accordingly, the notion of search here does not stand for an adaptive behavior of the agents but for population-level genetic mutation (Ganco & Hoetker, 2008:4; Dosi et al., 2011:13).

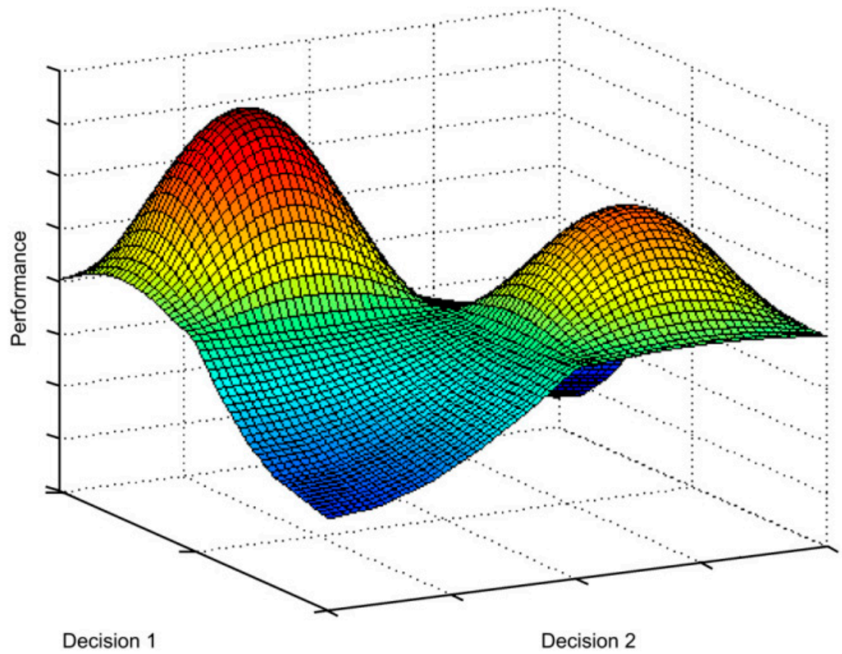

Figure 6: Performance landscape consisting of two dimensions with interaction
(Source: Rivkin & Siggelkow, 2006:597)

The scalable complexity and local optima featured by NK landscapes support research into contextual effects on path dependence in three ways:

1.) NK landscapes define a multitude of outcomes and specify their performance. By employing an NK landscape, the researcher therefore can mitigate the critique concerning the inefficiency property of path-dependent outcomes which even holds for recent simulation models of path dependence.[97]

2.) With respect to the configuration of the organizational environment, NK landscapes model complexity not merely as an effect arising from the number of elements to be deciphered by the learners but from the interaction of these elements which matches our definition of complexity.[98] The level of interaction between the environmental elements can be adjusted and

[97] See for example the simulation model of Petermann (2010) which deals with complementarity effects leading to organizational path dependence.

[98] See chapter 2.3 where we specify the organizational environment.

determines the structure of the landscape allowing us to inquire into the effects of different degrees of complexity.

3.) Path-dependent processes are non-linear, they can have multiple outcomes. In terms of NK landscapes, this can be visualized as the agents being drawn to different peaks, or in other words local optima, in the landscape.

In his review of organizational simulation models, Ashworth & Carley (2007:100) consider models of complex spaces as powerful theory-building tools. Since path dependence theory in some respects draws closely on complexity theory (Sydow, Schreyögg, & Koch, 2009:693), it should come as no surprise that NK landscapes offer an insightful framework to think about path dependence.[99]

In this chapter, we pointed out the usefulness of agent-based approaches for the emergent phenomenon of path dependence and further narrowed down our simulation approach to NK landscapes. After specifying the means by which to inquire into our research question, the subsequent chapter gives some indication as to how convincing simulation research is carried out and outlines the necessary steps.

3.4 Steps in Computational Research

This chapter aims at describing which steps are recommended for computational modeling research. The science how to do convincing computational research of social behavior is still in its infancy (Carley, 2009:57). This might be due to the aforementioned problem that computational modeling in the social sciences is still a rather seldom used methodological approach. Moreover, it resides uncannily between the more common empirical and theoretical guided research approaches. Important steps in computational modeling are therefore concerned with model verification which refers to the internal validity of the model and model validation which deals with its external validity.

Whereas the internal validity of a model alludes to a correct implementation of the simulation program, the external validity of a model must be considered with respect

[99] For a formal description of NK landscapes see chapter 5.2.1.

to its level of abstraction. More often than not, models of complex systems are to be understood as a sort of map to the real world, showing basic structures which give orientation. For instance, models can illustrate that simple processes can produce structures and outcomes we encounter in reality (Epstein & Axtell, 1996:4). Still, in the real world these processes are superposed with other influences.[100] Therefore Sterman (2004:846) questions if models can ever be validated. He gives an obvious reason for this in claiming that all models are incorrect while at the same time postulating that all theory that describes the world relies on abstractions and simplifications as models. Consequently, falsification, generally, does not get us very far. Like Kuhn (1970) and Lakatos (1974) explained, deciding rationally between different theories often is not possible, as theories are based on worldviews whose development follows similar mechanisms as described in our collective learning system and supposedly can lead to persistent inefficient outcomes.[101] Validation therefore must also be considered a social process in which the goal of modeling is to *"build shared understanding that provides insight into the world and helps to solve important problems"* (Sterman, 2004:850). Consequently abstract models are often difficult to validate but can still be helpful in guiding thinking. A very good example for a helpful model is March (1991) which has inspired research on organizational learning framing learning in terms of exploitation and exploration and pointing out some of its basic mechanisms. This model certainly is recognized in the research community as a valuable and helpful simplification.

Based on these considerations, in the remaining part of this chapter we give an overview which steps should be taken in computational research to arrive at a model which will be treated as at least providing reliable results in the tight boundaries of its specification. The following life cycle of computational modeling shows the different steps involved in simulation guided research.[102] It describes simulation research as moving from a theoretical model, via the computational model to the experimental model. Proceeding from one model type to the next always involves a set of activities typical for simulation research. The different phases of the simulation life cycle also

[100] See chapter 3.2.2.

[101] See on the development of scientific paradigms the simulations models of De Langhe & Greiff (2009); Weisberg & Muldoon, forthcoming.

[102] See also Davis, Eisenhardt, & Bingham (2007:482) for an overview of the different steps involved in computational research.

are connected showing that the researcher iterates between deductive reasoning in which he deduces the consequences of his model and inductive reasoning in which he makes sense of the generated data.

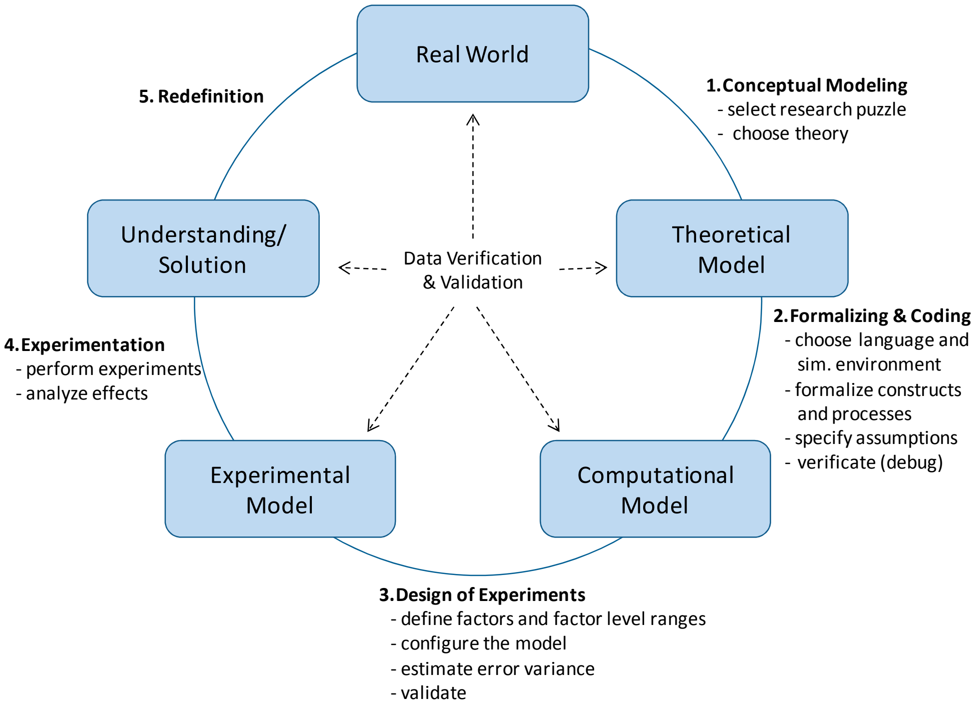

Figure 7: Life cycle of computational modeling
(adapted from Balci, 1998; Helmhout, 2006:10 and Wijermans, 2011:65)

The various stages in the cycle can be connected to the different chapters of this dissertation. In chapter 2, our theoretical model which builds on path dependence and organizational learning theory explains how the learning mechanism links an organization to its environment. After specifying our simulation approach in relation to the characteristics of our research phenomenon in chapter 3, we embark on designing a computational model. This step in chapter 4 involves reviewing how existing models in organizational learning relate to path dependence theory and is based on the dynamics identified in our theoretical framework. Our computational model, as described in chapter 5, integrates these dynamics. Here, we provide a formal definition of the computational model, focusing on its constructs and processes. We also briefly introduce simulation language and environment and describe how we verified the model, or in other words how we ensured that it works as it is expected to. We proceed to the experimental model in chapter 6. We establish the experimental model by defining factors and factor level ranges thereby setting the stage for the experiments to be conducted. As every model has random factors influencing the model outcome a single run of the model will commonly not provide us with reliable results (Gilbert & Troitzsch, 2005:25). In an estimation of the error variance, we determine a reliable basis concerning how often the model has to be repeated to provide statistically interpretable results (Lorscheid, Heine, & Meyer, 2011). On this basis, we enter the experimentation phase. The first experiment aims at validating the model. By running our model in specific conditions, we try to replicate results of models recognized in the research community and thus anchor the model in existing research. The following phase of experimentation encompasses exploring and describing the model behavior for the different defined settings of environmental complexity and turbulence. In the last step in chapter 7, we are concerned with interpreting the simulation results and discuss how they contribute to our understanding of organizational path dependence.

4 On the Way to a Computational Model of Path Dependence in Organizational Learning

In this chapter, we bridge the gap between our theoretical framework which highlights the path-dependent mechanism in organizational learning and the computational model of the theorized dynamics as described in chapter 5. For this purpose, we deal with two types of models which relate to the feedback loops in learning as described in our theoretical framework. In chapter 3, we clarified our methodological approach and pointed out why the NK approach is suitable for path dependence research. In the present chapter, we show how it can be used to model learning involving the individual level. For representing learning involving the organizational level, we consider the mutual learning modeling approach an appropriate tool. The question guiding us in this chapter is what we can conclude from these specific computational model types for our research focus on organizational path dependence and its environmental context.

In our theoretical framework, we emphasized that both individual learning and learning from the experience of others in social interaction are important for an analysis of path dependence in organizational learning. Mere individual enhancement of competence will not provide a homogeneous mindset among organizational members but lead to the presence of divergent mental models. Simply focusing on social exchange processes as some learning models do, provides a continuous convergence of mindsets but is hardly a realistic outlook on the individuals in the organization. Therefore, both learning processes involved in our theoretical outline can be considered to frame exploitation and exploration in terms of different dynamics. While social learning processes emphasize learning in social entities as a process of converging mindsets, the individual enhancement of competence builds on increasing capabilities and raising the opportunity costs of exploration or trying something new (Levinthal & March, 1993:106). Figure 9 gives an overview of modeling approaches which are able to represent these dynamics.

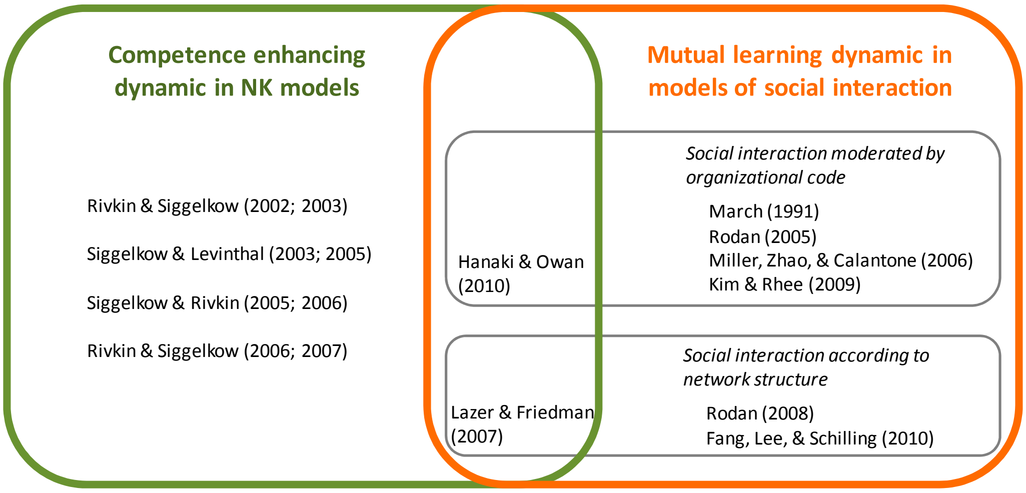

Figure 8: Computational models featuring individual competence-enhancing or mutual learning dynamics

In the overview, we discriminate between two general categories of learning models which either reflect the competence-enhancing dynamic in NK models or the mutual learning dynamic of social interaction.[103] The mutual learning framework includes models which consider learning as an interaction process between the organizational level, here often called the organizational code, and the organizational members as well as those models, which regard learning as direct interactions between organizational participants which happen along the lines of an informal network structure. The local search framework subsumes the models which picture learning as searching a problem landscape for good knowledge configurations. Recently, a few models have acknowledged the benefits to be gained from a unified perspective involving search as well as exchange processes in an organizational learning model.

In the following section we deal with each of these model categories in turn. We explain the specific basic dynamics in these models, how they relate to organizational path dependence and what answers can be gained from them for our research focus. We conclude this chapter by considering the interplay between the learning dynamics and speculate on their outcomes in complex and turbulent environments.

[103] We focus on models which have an intra-organizational perspective as opposed to those which model dynamics between organizations. Dynamics in which the learning agent represents an organization in itself, for example, have been modeled by Lant & Mezias (1990), Levinthal (1997), and Gavetti & Levinthal (2000).

4.1 Modeling Learning involving the Organizational Level: Mutual Adaptation

March‘s (1991) mutual learning model laid the ground for a number of models which explicitly consider the social side of organizational learning. The following chapter describes the basic dynamic of mutual learning models using March's model as a starting point. We consider this dynamic to be a useful representation of the feedback loop connecting the individual and the organizational level in our theoretical framework.[104] After this introduction, we link mutual learning to path dependence research focusing on the identified dynamic in the model. In order to work out the variables for describing the context inside the organization which influences learning, we continue by considering various extensions of the mutual learning model and relate the examined variables to the inherent dynamic in models of mutual learning. In the last chapter, we point to the missing element in March's (1991) model, learning at the individual level. We compare several processes in models of mutual learning which are supposed to increase variation in the system and discuss them in comparison with the process of individual learning.

4.1.1 Mutual Learning: The Dynamic in March's (1991) Model

The mutual learning model by James G. March (1991) very generally displays learning as a diffusion process of organizational knowledge among the individuals in the organization. At the heart of the model lies the interaction between the organizational and individual level which is influenced by the speed of knowledge diffusion.

The model assumes a very simple organizational structure in which individuals and an organizational code both are repositories of knowledge.[105] Knowledge resides in the heads of the organizational members, but on the organizational level it is accumulated in a supra-individual collective structure, the organizational code which reflects the

[104] See chapter 2.2.5.

[105] See chapter 3.1.2 on the beauty of simple models. This structure is sufficient to show the dynamics March (1991) intended to point out. More elaborated structures would emphasize different aspects which were not the focus of the original model or even make the model less transparent.

knowledge which is shared throughout the organization.[106] Organizational knowledge is distributed to the individuals solely via the organizational code. This socialization process influences the knowledge of the individuals and gradually brings them closer to the organizational knowledge. Simultaneously, the organizational code learns from the individuals in the organization. In contrast to the socialization process in which the individuals have to adopt organizational knowledge without questioning its correctness, the code only learns from the individuals whose knowledge has a closer correspondence with external reality than the code knowledge. Therefore, learning here is modeled as a process which changes how individuals and the organization perceive reality. The result of learning is a change in beliefs or cognitions. How accurately the organization or the individual perceives reality, or in other words how closely their cognitive representations match reality, determines the individual or organizational level of knowledge. To represent reality, March chooses a bit string which consists of m dimensions; each dimension can have the value 1 or -1. Consequently, m-dimensional bit strings form the representations of reality on the code and individual level. In this simple model, code and individuals are solely characterized by their bit strings which show their state of knowledge.

Basically, March (1991) defined two input parameters to show the intended dynamics resulting from the interaction of the organizational and individual level, the speed of learning *from* the code or, in other words, the effectiveness of the socialization process and the speed of learning *by* the code or how fast the organization learns from its members. Different configurations of the input parameters can then be examined concerning their impact on the knowledge level of the organization and the average knowledge level of the individuals in it. The knowledge level is determined as the percentage of the dimensions of reality the organization figures out correctly.

With a simple specification and few parameters, the model succeeds in inquiring into the dynamics of learning occurring simultaneously at different levels. Organizational

[106] March (1991:73) defines the organizational code as the accumulated organizational knowledge which is stored by the organization in rules, procedures, and norms. More explicitly, Arrow (1974:53-55) refers to the organizational code as knowledge structures inside the organization which guide the acquisition and interpretation of new knowledge. Codes reflect the history of an organization, learning from a code is considered to be an act of irreversible investment for the individual. As a consequence of adapting to the code, the individual becomes less efficient in gaining information that does not fit into the code. See also chapter 2.2.3 on the collective and modular view of organizational learning.

learning here is conceived as matching the organizational knowledge with external reality as the code learns from the individuals who are more knowledgeable. However, learning from the code is not guided by alignment with reality but solely with the system's shared values and beliefs. The individuals learn from the code's representation without further matching it with reality. Consequently, every time step of the simulation brings about more consistency between the organizational knowledge and the knowledge of the individuals. The elimination of differences between the code and the individuals decreases the variance of knowledge in the system. The learning process stops when one common solution has been reached, in other words when all individuals and the code have the same representation of the external reality.

The basic dynamics can be uncovered by experimenting with the different learning speeds. The experiments show conflicts between short-run and long-run results of learning as well as between results of individual and organizational learning. Generally, higher rates of learning lead to an earlier convergence of beliefs; a common organization wide representation of reality will be established sooner. However, the different rates concerning learning from and learning by the code have different consequences for the system (March, 1991:74-75).

While the rate of learning *from* the code impacts the time available for organizational learning (or, in other words, the time for the different beliefs to converge), learning *by* the code influences the intelligence of organizational learning. With higher learning rates the code is able to improve its knowledge faster and to reap a greater benefit from the knowledge of the organizational members. Combined with a low socialization rate which gives the code more time to learn from the organizational members before the convergence on one unified belief-set, the organization will achieve the best learning result.

Figure 9 exemplifies this dynamic in systems of mutual learning. Central to it, therefore, is its internal variety in beliefs about external reality. As long as the system possesses at least some internal variety in knowledge, it continues to learn (Rodan, 2005:410, Miller, Zhao, & Calantone, 2006:714; Kim & Rhee, 2009:13). The settings of the learning process involving the organizational level or code are decisive for the development of the internal variety of beliefs.

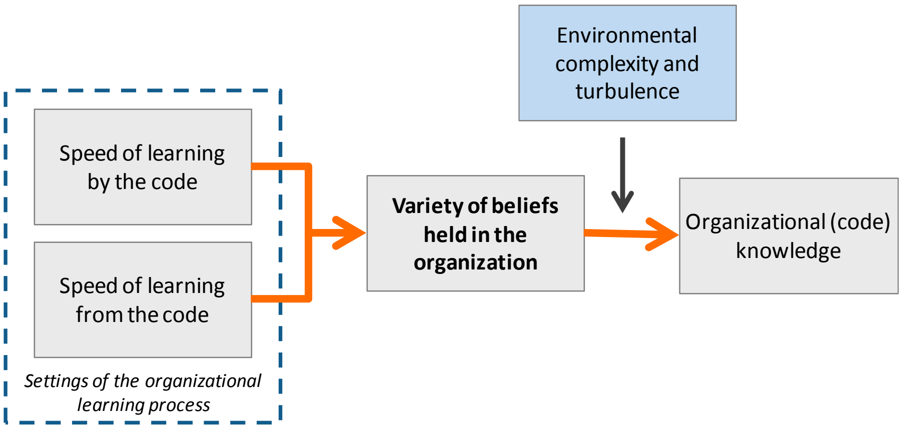

Figure 9: Dynamic of mutual learning
(Adapted from Kim & Rhee, 2009:14)

The organizational environment is seen as moderating the relationship between the variety in beliefs and the organizational knowledge or in other words the learning success of the organization (Kim & Rhee, 2009:13). The organization can only keep on learning if it still has belief variety to draw upon. Based on the variety of beliefs, the organizational level selects the beliefs of the better performers and combines them to improve organizational knowledge. Environmental complexity, here considered in terms of the mutual learning model as a mere increase in environmental dimensions without interaction effects and as such local optima, makes learning for the code more difficult and consequently lowers organizational knowledge (Miller, Zhao, & Calantone, 2006). Environmental turbulence, in turn, interrupts the learning process. Since the knowledge variety declines while the organization learns and the system's adaptability is directly related to its belief variety, frequency and scope of the environmental change are highly significant for the learning success (Kim & Rhee, 2009).

As we will see later on,[107] the internal variety is the crux to all dynamics in mutual learning models. It is also a crucial notion for path dependence which we deal with in the following chapter. Similar to Burgelman's (2002) argumentation, processes which reduce variation in the system can be considered exploitative whereas processes which increase variation can be seen as explorative. In his model, March (1991) probes the

[107] See chapter 4.1.3, where we are concerned with the extensions of March's (1991) model, and chapter 6 for our own experiments with the integrated model featuring a combination of mutual learning and individual learning.

effects of the speed of learning on the internal variety of the system. Thus, fast learning is here connected to exploitation, whereas slow learning, counter-intuitively as one would think, is connected to exploration. We will see in a subsequent chapter[108] that work which builds on March's (1991) model can always be connected to this mode of functioning. Basically, extensions of his model deal with different aspects which directly impact the internal knowledge variety of the organization. In the following chapter, we first clarify the connection between the dynamics of internal variety and organizational path dependence.

4.1.2 Internal Variety and Path Dependence in Models of Mutual Learning

The mutual learning model deals with the social side of organizational learning. Learning is pictured as an interaction process between the individuals in the organization and the organizational level which changes the knowledge state of the individuals and enables organizational learning. The exchange of knowledge not only enhances organizational learning, it also diminishes the internal variety of knowledge in the organization finally resulting in a commonly shared, homogenous mindset. We explain in the following section why a homogeneous outlook on the world is an indicator for organizational path dependence.

Organizations are capable of acquiring much more information than any one individual. But as organizations surmount the limitations of an individual's capacity, they have to make knowledge from different sources mutually understandable. Arrow (1974) claims that for this reason there is a need for codes in organizations.[109]

> *"The need for codes (…) imposes a uniformity requirement on the behavior of the participants. They [the participants] are specialized in the information capable of being transmitted by the codes, so that they learn more in the direction of their activity and become less efficient in acquiring and transmitting information not easily fitted into the code. Hence, the organization itself serves to mold the behavior of its members."* (Arrow, 1974:56-57)

[108] See chapter 4.1.3.

[109] Carley (1992:35) further illustrates the function of the institutionalized organizational memory as acting as a buffer zone which focuses the learning of the individuals and helps to prevent mistakes.

Due to the imposed uniformity, internal variety in knowledge in the organization decreases. Miller (1993:118) implies that the escalating simplicity can have dismal consequences for an organization. Generally, simplicity in his approach describes a special kind of inertia which in particular refers to limited variety at a point in time compared to limited inter period variety. Miller (1993) explains the problem caused by simplicity by alluding to the law of requisite variety. A system in need of regulating itself against environmental variety needs an internal variety that is at least as high as the experienced external variety (Ashby, 1956:207; Buckley, 1968:495). Thus, organizations which have become too simple are unable to cope with the complexity of external reality. Weick (1979:189) gives a clear explanation. A simple process which is used to interpret complicated data will result in most of the information going unnoticed. Paradoxically, a uniform mindset in an organization has its benefits; it eases communication and coordination and, thus, seemingly contributes to an increase in efficiency.[110] It is only when the organization is confronted with complexity and change of the environmental conditions that the dark side of limited internal variety begins to show.

Closely related to the implications drawn from the law of requisite variety are the findings of research on the absorptive capacity of organizations. Absorptive capacity captures the ability of the organization to integrate external knowledge. Knowledge already present in the organization affects the organization’s ability to assimilate new information and translate it into internal knowledge (Lane, Koka, & Pathak, 2006:833; Argote & Greve, 2007:342). Variety in knowledge inside the organization is a prerequisite to access different kinds of external knowledge. In the March (1991) model, internal variety is linked to the organization’s ability to determine the external reality. Cohen & Levinthal (1990:128-129) specify the absorptive capacity of an organization in close relation to the heterogeneity of its internal knowledge. They consider the organizational ability to assimilate and apply external knowledge as a function of prior related knowledge inside the organization.[111] As outlined in

[110] The increasing returns mechanism of mutual learning is derived from the interactive processes between a large number of agents. It can be considered to lie in the emergent mindset on the macro or system level. For a reflection on the connection between self-organization and increasing returns, see Petermann (2006:61-62).

[111] For an overview of different conceptualizations of absorptive capacity see Zahra & George (2002:188). The theoretical arguments of the compared approaches concerning absorptive capacity tend to support the original definition given by Cohen & Levinthal (1990).

chapter 2.2.4, individuals are the sensors of an organization to its environment, they acquire new knowledge. The absorptive capacity of an organization is tightly linked to the absorptive capacity of its members but it is not equal to it. The meaning of absorptive capacity does not merely involve the acquisition of new knowledge but also the ways the organization applies and exploits it, or in other words, *"the character and distribution of expertise within the organization"* (Cohen & Levinthal, 1990:132). Therefore, a fast and thorough socialization of members to the existing organizational code would impact the organizational absorptive capacity negatively. Cohen & Levinthal (1990) argue that it is the diversity of knowledge inside the organization which keeps the organization connected to its environment.

> *"In a setting in which there is uncertainty about the knowledge domains from which potentially useful information may emerge, a diverse background provides a more robust basis for learning because it increases the prospect that incoming information will relate to what is already known."* (Cohen & Levinthal, 1990:131)

A diverse background of knowledge held in the organization facilitates understanding and assessing changes in the environment. The organizational members incorporate new knowledge into the organization, their personal knowledge and their mental models determine how the organizational knowledge environment will be searched (Lane, Koka, & Pathak, 2006:854).[112] Absorptive capacity is therefore often described as a learning capability (Cohen & Levinthal, 1990:136; Lane, Koka, & Pathak, 2006:839). High absorptive capacity implies a high learning ability in the organization and thus adaptability to different environmental conditions. In a sense, low absorptive capacity implies narrow worldviews and focused skills inside the organization which are also the conditions that are conducive to the formation of simple monolithic cultures and strategies (Miller, 1993:119-129).[113]

We conclude that the dynamic in mutual learning connects closely to the concepts of simplicity (Miller, 1993) and absorptive capacity (Cohen Levinthal, 1990). Since

[112] This viewpoint emphasizes a different role of the knowledge variety than the one considered in March's (1991) model. The knowledge variety in the organization must not only be recognized as a source for the code to draw upon but also as a diversified basis for the individual learning processes. We deal with this aspect in chapter 4.3.

[113] Absorptive capacity is a learning capability, but it is also a learned capability. As a learned capability, Cohen & Levinthal (1990:136) describe its development as history or even path dependent. Absorptive capacity develops as a product of prior learning and problem solving and therefore itself evolves cumulatively (Lane, Koka, & Pathak, 2006:838).

learning as a social exchange process leads to decreasing internal variety, simple monolithic structures and low absorptive capacity can be considered consequences of this process. Both indicate that the organization is unable to cope with changes in the organizational environment. Processes of mutual learning therefore threaten the organization with becoming inflexible and at least potentially inefficient as a consequence.

With the speed of learning from and by the code, March (1991) used highly general variables to specify how the settings inside the organization affect learning. In order to determine more closely how to model the organizational context of path-dependent learning, in the following chapter we discuss various extensions of March's (1991) model. For this purpose, we provide an overview of different aspects of the organizational context which have been found to influence the dynamic of internal variety and relate these findings to the variables in the original model.

4.1.3 The Organizational Context and the Dynamic of Internal Variety

Exploration and exploitation in the mutual learning approach are closely connected to the internal knowledge variety in the system. Forces which lead to less variety can be considered exploitative whereas those which increase variety in the system, or at least preserve it, can be regarded as explorative (Burgelman, 2002). That is why, in March's (1991) model, fast learning represents exploitative behavior. The dynamic which underlies the decrease in internal variety can result in a path-dependent end state which is characterized by a homogeneous mindset throughout the organization. As the organization loses its heterogeneous viewpoints, its ability to assimilate new knowledge in the organizational environment deteriorates.

Due to its well specified dynamic, which is applicable to a broad range of organizational learning aspects, the original mutual learning model has inspired several extensions. Mostly, these identify different forces inside the organization which affect the dynamic of decreasing internal variety in mutual learning.

In chapter 4, we gave an overview of the intra-organizational computational modeling approaches which are considered to reflect the two learning processes as specified in our theoretical framework. The mutual learning models here are further divided according to how they specify the structure inside the organization. Some models directly build on March's organizational lay-out explicitly modeling an organizational level of learning, while others model mutual learning as a direct knowledge exchange between the organizational members which is not moderated by the organizational code. We note that the different attitudes towards the importance of an organizational layer of learning,[114] do not influence the basic model dynamic of decreasing internal variety. They mainly offer the possibility to explore different aspects of the exploration-exploitation tension. Kim & Rhee (2009) introduce the notion of vertical socialization where the organizational code is involved and horizontal socialization for the learning processes between individuals in the organization. Even if in horizontal socialization learning of the individuals is not moderated by an organizational code both socialization processes are bound to lead to an alignment of organizational knowledge.

Basically, mutual learning models show that an organization is capable of learning in situations where individuals are not (March, 1991; Rodan, 2005). Extensions of the mutual learning model often concentrate on altering the learning processes in the model. In the following, we show that different characteristics of organizational life influence the described dynamic in organizational learning and, thus, further emphasize that the underlying logic of the mutual learning model refers to a very broad range of organizational phenomena.

[114] See on chapter 2.2.3 the different levels of learning.

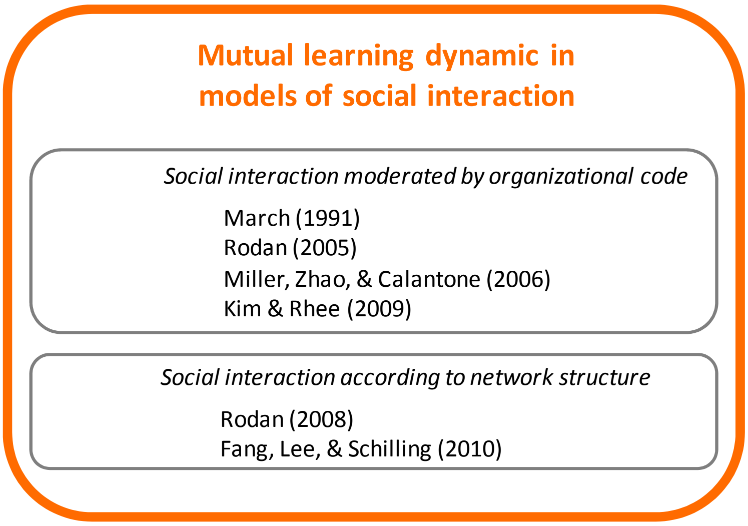

Figure 10: Computational models featuring the dynamic of internal variety

For this purpose, we briefly review the extensions of the mutual learning model as shown in Figure 10 and give a structured overview which organizational aspects have been found to produce similar effects. The discussion builds on the two processes involved in March's (1991) model. First, we refer to extensions of March's (1991) model which focus on altering the process by which the organizational level learns from the individual level or in other words how the organization selects knowledge. Second, we consider the extensions which concentrate on the process which distributes knowledge to the individuals.

4.1.3.1 Effects of Learning by the Code on Internal Variety

Building on the structure of the March (1991) model, Rodan (2005) researched the impact of different selection criteria for incorporating knowledge into the organizational code. While in March (1991) the code learns from all organizational members who perceive the environment more correctly than the code itself, Rodan (2005:413-414), instead of performance, introduces tenure and an emphasis on longer performance histories as the relevant criteria to be selected for transferring knowledge to the code. He also considers a stringency parameter as a threshold of performance to be admitted for knowledge transfer. The different organizational policies of aggregating knowledge into the code show an important aspect of the socialization process. The aggregation of knowledge into the organizational code depends on how the organization selects from its variety of knowledge. Promotion based on tenure rather than performance, consequentially, leads to a decline in organizational knowledge (Carley & Harrald, 1997:325-326; Rodan, 2005:420-421). Giving a greater weight to past performance than to current performance for selecting knowledge shows a similar effect: the learning success of the organization declines. For setting the stringency parameter, a middle ground proved to be the best strategy for the organization (Rodan, 2005:422). Very high performance standards for selecting knowledge from the internal knowledge pool proved to be counter-productive for learning success aswell as too weak standards. Behind this clearly stands the dynamic of the internal variety of the group of individuals the code chooses for learning. If the knowledge variety of this group is very low, and accordingly the stringency parameter for selection is very high, the organization misses opportunities to learn.

4.1.3.2 Effects of Interpersonal Learning and Network Structure on Internal Variety

Similar dynamics were uncovered in models which integrate horizontal socialization, or in other words direct interpersonal learning, into the mutual learning model. Miller, Zhao, & Calantone (2006) and later Kim & Rhee (2009) extended March's (1991) model by incorporating the knowledge exchange process between the organizational members as a further learning process in addition to the two processes of learning *from* and learning *by* the code. Thus, individuals in this model are socialized via the organizational code and by the interaction with their peers. In the interaction with their peers, it matters how the individuals are connected to each other. While not varying the social network type between the organizational members as was done by more recent models (see Rodan, 2008; Fang, Lee, & Schilling, 2010), Miller, Zhao, & Calantone (2006) differentiate between close and distant contacts of the organizational members.[115] Generally, interpersonal learning has the same effect on internal variety as learning from a code. Not surprisingly, both processes work in the same direction,

[115] The agents in Miller, Zhao, & Calantone (2006) are situated on a grid, each agent having four close neighbors. For approaching distant contacts, an agent randomly picks four individuals from the organization and selects the best one to learn from.

although learning from the code is the faster way of exchanging knowledge since the code has access to all organizational members. Compared to learning from the code, interpersonal learning therefore can be dealt with as a slower form of socialization.[116] Interestingly, Miller, Zhao, & Calantone (2006) had earlier asserted that the speed of interpersonal learning is moderated by the network structure between the organizational members. In their model, learning from distant neighbors increases the average number of interpersonal links, comparable to the rewiring of nodes in small world networks. It, thus, contributes to exploitation as it supports fast learning.

Rodan (2008) and Fang, Lee, & Schilling (2010)[117] in their models of solely interpersonal learning in networks found similar effects. First, collective learning can also be attained by solely interpersonal learning; comparable to Miller, Zhao, & Calantone (2006), the researchers found that it has a similar function as learning provided by an organizational code (Rodan, 2008:244). With interpersonal learning, the characteristics of the social network influence the knowledge exchange.[118] The connections to other individuals in a network provide access to information and therefore enable learning. On the other hand dense networks also raise conformity pressures and limit learning to certain areas of expertise; networks therefore constrain experimentation. Rodan (2008) therefore claims that there seems to be a moderate level of isolation of individuals in social network which serves best for organizational learning. Consistent with this observation, Fang, Lee, & Schilling (2010) found out

[116] Miller, Zhao, & Calantone (2006:719) in their model of parallel socialization by the code and interpersonal learning already found out that setting the learning rate from the code to zero for achieving an exchange of knowledge between the organizational members solely via direct interpersonal learning produces the best results. Keeping in mind the positive effects of slow learning from the code (March, 1991), interpersonal learning takes the role of a slower form of socialization. Fast interpersonal learning is here found to have similar negative effects as fast learning from the code. Kim & Rhee's results (2009) confirm many of the effects of a joint application of vertical and horizontal socialization processes in an organizational learning system as found by Miller, Zhao, & Calantone (2006).

[117] Fang, Lee, & Schilling (2010) use an organizational environment which closely resembles the NK approach. Still, we subsume their work under mutual learning models as their model does not encompass processes of individual competence-enhancing learning.

[118] Rodan (2008) also explores the effect of different individual heuristics for choosing the individuals to interact with in your network. The unfolding dynamics are comparable with the results for knowledge selection processes for an organizational code (see Rodan, 2005). Although selecting the best performing contact proved to be a good strategy, the best strategy was a striving for a consensus between your contacts. Although this approach does not strongly enforce the diffusion of the best solutions present in the system, it helps to preserve internal variety and increases the time available for the organization to learn.

that in small world networks moderate amounts of cross-group links provide the highest learning results.

The described extensions of March's (1991) model capture different organizational aspects which all affect the dynamics of internal variety of knowledge. Socialization processes in which the organizational members learn from an organizational code or from the interaction with their peers in general contribute to a unification of their different views of the world. How knowledge is selected for being incorporated into the organizational code and transferred between the individuals, as well as the structure of the network between the organizational members in solely interpersonal learning, displays a very close connection to the important parameters in the original model. Here, the speed of socialization directly impacts how fast the organization loses its internal variety. The heterogeneity of the group of members which the organizational code selects for learning, or the network structures of the interpersonal network, are mainly moderators of the original parameter: the speed of learning.

With respect to our model, this confirms that we can build the knowledge exchange process in the organization on the original configuration of March (1991), employing solely learning by the code as long as we do not aim to probe into the effects of network structures in the organization or spatial aspects of the learning processes. Similarly we conclude that for our model, the speed of learning suitably characterizes the context inside the organization in which mutual learning takes place.

The subsequent chapter makes the transition to the discussion of individual learning in chapter 4.2. As individual learning is supposed to increase the knowledge variety in the organization, we consider which extensions of the mutual learning model introduce processes which counteract the dynamic of decreasing variety. We describe their effects on the dynamic of mutual learning and identify how they differ from individual learning.

4.1.4 Variety-Increasing Processes in Models of Mutual Learning: A Comparison

The mutual learning model (1991) gives a very good account of the dynamic in learning which involves the organizational level. Its parameters, the speed of learning from and by the code, encompass many different aspects which impact learning and therefore are suitable for a general inquiry into different settings of mutual learning in organizations. With relation to our research focus, two important aspects are missing. Firstly, the organizational environment is not suitably specified for inquiring into the effects of complexity and path dependence. Secondly, the individual learning process is left out of the picture. In the following section, we deal with these aspects in turn. In relation to the missing individual learning process, we consider what can be derived from extensions of the mutual learning model which inquire into different processes impacting on the individual level. These processes presumably resemble the individual learning process in a characteristic feature; they are bound to increase the variation in the mutual learning system.

With regard to the first aspect, the specification of the organizational environment in models of mutual learning, we notice the following: Models of mutual learning depict the organizational environment in a highly abstract way.[119] The organizational environment is represented as a bit string of m elements which can either have the value of -1 or 1. These values do not capture any positive or negative rating of the concerned environmental dimensions; they are simply conditions which the organization aims to find out. Organizational knowledge as well as individual knowledge likewise is represented as a bit string of similar length.[120] The learning success of an organization is derived directly from the closeness of the organizational representation to external reality, or in other words in how many elements the organization succeeds to find out the configuration of external reality (March, 1991; Rodan, 2005; Miller, Zhao & Calantone, 2006; Kim & Rhee, 2009). Here, the difficulty of the learning task is determined solely by the length of the bit string.[121]

[119] See on this also chapter 3.3.

[120] The bit string representing the organizational or individual knowledge consists of -1, 0 and 1 and represents what the organization or the respective individual assumes the reality to be like. In case of a 0, the organization or individual is unsure about the environmental status on this special dimension.

[121] Miller, Zhao, & Calantone (2006:710) varied the number of dimensions to reflect on the difficulty of the learning task.

The length of the bit string defines with how many elements the agent has to deal with but it does not account for the interaction effects between environmental dimensions which causes problem complexity. In incremental learning, it is surely possible to figure out one dimension after the other. It is only the interaction of dimensions which makes it necessary for the learner to consider dimensions simultaneously in order to figure out the environment. Having to deal with many elements simultaneously is what defines complexity in the first place (Anderson, 1999). We deal with this specification of complexity and its interrelation with individual learning in greater detail in chapter 4.2.1 and 4.2.2.

We identified a second aspect which is missing for an inquiry into path-dependent organizational learning. March's (1991) model considers mutual learning as a process of convergence between the organizational beliefs and the state of the external environment. The convergence is guided by the selection process on the organizational level; experiential learning on the individual level is not considered. Still, many approaches in organizational learning stress the role of individual learning and especially its importance for the acquisition of knowledge about the environment (Hedberg, Nystrom, & Starbuck, 1976; Burgelman, 2002; Argote & Miron-Spektor 2011) as it is also reflected in our theoretical framework.[122] Here, the organizational learning process is supplemented by a learning feedback loop on the individual level in which the individual gathers experience in close connection to the external environment. The process of individual learning incorporates knowledge from the outside into the organization and hence introduces variety, but it is also subject to specific limitations stemming from its path-dependent nature. In the mutual learning model, as well as in several extensions of it, we find processes which impact on the individual level: personnel turnover and individual experimentation. These processes have an important point in common with individual learning in our framework; they introduce variety into the organization. It is worthwhile considering their influence on the behavior of the organization for deriving implications concerning the expected outcome of our model.

March (1991) introduced turnover as a variety-increasing process into his model, an approach which was later also followed by other papers (Rodan, 2005; Kim & Rhee,

[122] See chapter 2.2.5 and Figure 3.

2009; Fang, Lee, & Schilling, 2010). Turnover is modeled by simply replacing individuals in the organization with new entrants who are characterized by random beliefs. New entrants as such are simply individuals who are not yet socialized to the organizational way of perceiving reality.

Besides turnover, Rodan (2005) introduced other variation increasing processes into a mutual learning model, regimes of individual experimentation. Here, the individual is capable of varying his own knowledge without involving the organizational code. For Rodan (2005:410), experimentation of the individuals encompasses aspects like risk-taking or foolishness (March, 1988). In the context of individual experimentation, foolishness is simply experimentation which is unconstrained by individual or organizational restrictions. In comparison with the two remaining experimentation regimes, the distinction will become clear. In organizationally constrained variation, the organization forces the organizational reality onto its members and thus, limits experimentation to areas where the organizational knowledge does not seem to be mature or reliable. In self-restrained experimentation, individuals focus their learning on areas where they themselves feel that their knowledge might be insufficient (Rodan, 2005:411-412).[123]

Both processes - turnover and experimentation - introduce variation in beliefs into the organization via the individual level. As the new beliefs contain learning potential for the organization the organization gains adaptability. Variation increasing processes in models of mutual learning therefore always refer to preserving the ability of the organization to react. This is important if the organizational environment undergoes changes. Without these processes, changes of the organizational environment degrade organizational knowledge until it shows a random relationship to the state of reality (March, 1991:79-80; Rodan, 2005:419-420; Kim & Rhee, 2009:22; Fang, Lee, & Schilling, 2010:632). We can therefore conclude that if an organization is confronted with environmental change, it depends on its variety generating mechanisms.

[123] Similar to March (1991), the code or the individual's knowledge is modeled as a vector of defined length whose elements can take on the values 1, 0 or -1. In case of organizational or self-restrained experimentation, individuals experiment only with the elements on which the organization's knowledge (or in the case of self-restrained experimentation, their own knowledge), is 0 and therefore reflects uncertainty concerning the state of the organizational environment.

From comparing the different variety generating processes we can conclude their effects on organizational learning. The three ways of individual experimentation impact internal variety in different ways. While the constrained ways of experimentation prove to be of little effectiveness for learning, unconstrained experimentation or foolishness generally is the most beneficial mode of experimentation and the only one that upholds learning if the environment encounters constant change. Foolishness closely resembles personnel turnover. Like personnel turnover, the unconstrained mode of experimentation shows a U-shaped relationship with the learning success of the organization (Rodan, 2005:419; Fang, Lee, & Schilling, 2010:634-635). With too little turnover, variety in an organization drops beneath the level needed to cope with external change. Too much turnover on the other hand, due to the sheer number of interruptions, makes learning impossible (Fang, Lee & Schilling, 2010:635). We can thus expect variety-increasing mechanisms which merely randomly vary beliefs to have two effects. As a first order effect, they decrease the average knowledge of the individuals in the organization. The second order effect stems from the infused variety and positively impacts on organizational knowledge (Kim & Rhee, 2009:19). It holds mainly for processes which do not restrain variation and limit it to certain areas (as do the constrained modes of experimentation).

With individual learning, we introduce a process into the system which features intelligent behavior on the side of the organizational members. March (1991:75) himself referred to the organization in his model of mutual learning as a closed system. Even if introducing random variety-increasing processes in these systems opens the system up a little, it is still closed with respect to its connection to the environment. The adaptation to the environment happens only indirectly via the selection process of the code. Individuals are not supposed to learn from their own experience. With individual learning, the organization becomes an open system as the individuals are able to perceive the organizational environment. As individual learning differs from random variety generating processes in important ways, we can expect it to show different effects in the interaction with the dynamic of mutual learning. Table 6 gives an overview of the differences between turnover and individual learning. Although both have a similar function with respect to introducing variety on the individual level of the learning system, they show different characteristics.

Differences between variety introducing mechanisms	Personnel turnover	Individual learning
Preservation of variety	indefinitely	path-dependent dynamic
Interaction with mutual learning mechanism	independent	benefits depend on belief variety
Average knowledge of organizational members	decreases	increases

Table 6: Comparison of variety generating mechanisms: personnel turnover vs. individual learning

Turnover is thought to preserve variety indefinitely. One could claim that it is imposed from the outside on the organizational system. Individual learning in turn show its own path-dependent dynamics and is therefore also subject to the danger of locking-in.[124] Turnover does not interact with the mutual learning process, its effectiveness is not influenced by the process of knowledge convergence in the organization. For individual learning this is different. Its effectiveness for the organization depends on the existing knowledge variety in the organization. Consequently, we can assume that with individual learning we do not experience the first order effect as observed with turnover (Kim & Rhee, 2009:19). Individual learning is not thought to decrease the average knowledge of organizational members but improves it.

Mere mutual learning models have a limited view on organizational learning. As we pointed out in our theoretical framework[125], the individual level of organizational learning in particular is not sufficiently highlighted. Individuals are the sensors of the organization to its environment. That is why we can expect that the way they learn impacts internal variety in an organization. Simply modeling turnover as the only variety-increasing mechanism neglects the learning capacity of the organizational members. In this regard, Kim & Rhee (2009:35) suggest extending the approach by introducing other learning processes into mutual learning models. Fang, Lee & Schilling (2010:637) and Miller, Zhao, & Calantone (2006:719) in turn point

[124] We explain the path-dependent dynamic of individual learning in detail in chapter 4.2.

[125] See chapter 2.2.5.

more to the importance of testing mutual learning models for different contextual variables.

In the next chapter, we clarify how the specifics of individual learning are taken on in the NK framework and how this approach is able to reflect the characteristics of individual learning and its path-dependent nature.

4.2 Modeling Learning on the Individual Level: Search Processes in an NK Framework

In contrast to the previously described mutual learning model which deals with the social side of learning and the exchange of knowledge between the individuals in an organization, in the following section, we focus on the way an individual increases his knowledge without building on the experience of others. Here, we are concerned with clarifying how to model individual learning as represented by the first feedback loop in our theoretical framework[126] and discussing the modeled dynamic. In his study of designing economic agents, Arthur (1993) describes that individual learning in situations in which the optimal solution is difficult to identify often leads to path-dependent results. To demonstrate this, he models learning as an iterated multi-choice problem in terms of a stochastic learning algorithm. The difficulty encountered in finding the best solution present in the model is connected to the stepwise fashion of the learning process of the individual; the agent has to learn about the different present solutions by increasing his experience of them which is captured in a probability vector.[127] With the advantage of explicitly considering environmental complexity and local optima as specified in chapter 3.3, NK landscape models similarly can be used to model individual learning as a stepwise process in which each step depends on the history of the preceding ones.

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[126] See chapter 2.2.5.

[127] Arthur (1993) does not deal with environmental complexity. He considers the learning problem to be difficult if the reward differences between the three alternatives are difficult to discern. The difficulty is represented by a parameter which specifies the step-size of learning. Whereas large steps makes differences between the alternatives hard to notice, small steps makes closing in on a non-optimal alternative slow enough to be noticed.

In the following chapter, we introduce how this competence-enhancing individual learning can be modeled in NK landscapes. Similar to the preceding chapter on the social side of learning, we describe the basic dynamics at work in the NK approach, connect them to the concept of path dependence and finally explain which implications can be derived from NK models in organization theory for our research focus.

4.2.1 Individual Learning: The Dynamic in the NK Landscape Model

Additional to learning from the experience of others, organizational members change their knowledge based on personal experience. This learning process is strongly affected by their cognitive abilities and the characteristics of the knowledge to be accessed. Besides their general adequacy for research into path dependence and complexity, as pointed out in chapter 3.3, NK landscapes provide the surroundings for modeling individual learning. Individual learning here can be reflected in terms of how the agent walks the landscape.

Ackermann (2003) describes individual learning as being characterized by two features: First, individual learning follows a learning trajectory; learning is imprinted by past knowledge which guides the acquisition of future experience. Second, individuals are limited in their ability to perceive the environment; they are able to consider only a small scope of alternatives.[128] Because of the cognitive limitations, learning of individuals takes place in the close neighborhood of their current representation. This makes the current representation the frame of reference for future learning (Levitt & March, 1988:328-329) and also points to the reason why this type of learning often is referred to as myopic search (Cyert & March, 1963).[129] As individuals gather experience in the close temporal and spatial proximity of their actions, learning from experience generally will lead to an increase in competence in

[128] See the individual learning process in our theoretical framework in chapter 2.2.5.

[129] Argote & Greve (2007:338) refer to myopic search as a more specific version of bounded rationality.

particular fields and, as a result, to a narrowing focus and specialization (Levinthal & March, 1993:97).[130]

As implied by the concept of bounded rationality, the environment plays an important role in relation to the nature of the learning process.[131] Uncertainty and complexity blur the individuals' assessment of the environment leading to a systematic gap between the individuals' cognitive ability and the requirements of the external reality. Thus, the gap is defined by the difficulty of the learning task which generally is a feature of the knowledge to be acquired and the abilities with which the individuals are endowed (Dosi, Marengo, & Fagiolo, 2003:11). The cognitive limitations impose a boundary on the knowledge complexity that individuals can handle. Increasing knowledge complexity, thus, makes the cognitive deficits of individuals more pronounced (Ocasio, 1997:187-188).

NK models are able to reflect the cognitive characteristics of individual learning and furthermore to account for the interaction of individual learning with the complexity of the environment. We can think of individual learning in an NK model as the way the agent searches for solutions to the given problem, or to stick more closely to the illustration of the complex problem as a rugged landscape (Levinthal, 1997),[132] as the way the agent walks the landscape. Individual learning builds on the current knowledge state of the individual, the individual can neither overlook the complete solution space nor is she able to significantly alter her knowledge state in small time periods. Individual learning proceeds incrementally.[133] In terms of learning in NK landscapes, the learner is neither able to overlook the complete landscape and identify the optimum, nor is she able to jump in the landscape which would be synonymous with large alterations of her knowledge. In contrast, if we act on the assumption that

[130] The representations of the organizational members are not only impacted by their individual cognitive processes, but also by processes of social cognition. Organizational knowledge, as a cognitive map, frames the knowledge acquisition of the individuals (Walsh & Ungson, 1991:61; Dosi et al. 2011:37). We deal with the interaction of the individual and organizational level learning processes in chapter 4.3.

[131] Bounded rationality simply implies that individuals lag behind complete rational behavior which would encompass knowledge about all contingencies, oversight of the entire decision tree and a correct assessment of the utility evaluations of all mappings between actions and their outcomes (Dosi, Marengo, & Fagiolo, 2003:9).

[132] See chapter 3.3 for an explanation of NK spaces as rugged landscapes.

[133] For a classification of problem solving as knowledge formation see Nickerson & Zenger (2004:618-619).

the learner is fully rational, she would be able to overlook the complete problem space and as a result chose the global optimum. Learning in this case would become trivial (Ganco & Hoetker, 2008:9).

In consequence, how the learning process unfolds is tightly connected to the cognitive limitations of the individual. In the NK approach, the local search dynamic is used to reflect the tightly bounded nature of learning (e.g. Siggelkow & Rivkin, 2005; 2006; Lazer & Friedman, 2007). The agent learns by altering only a small portion of her representation in each time step. Conducting this so called local search,[134] the agent changes just one bit of the bit string which represents her knowledge state about the world thereby trying to find a better combination. The agent thus builds on her current knowledge and in a stepwise fashion increases her knowledge about the state of the environment. But as she only oversees the neighborhood of her current position in the landscape, once she has climbed a local hill, the learning process is bound to terminate.[135]

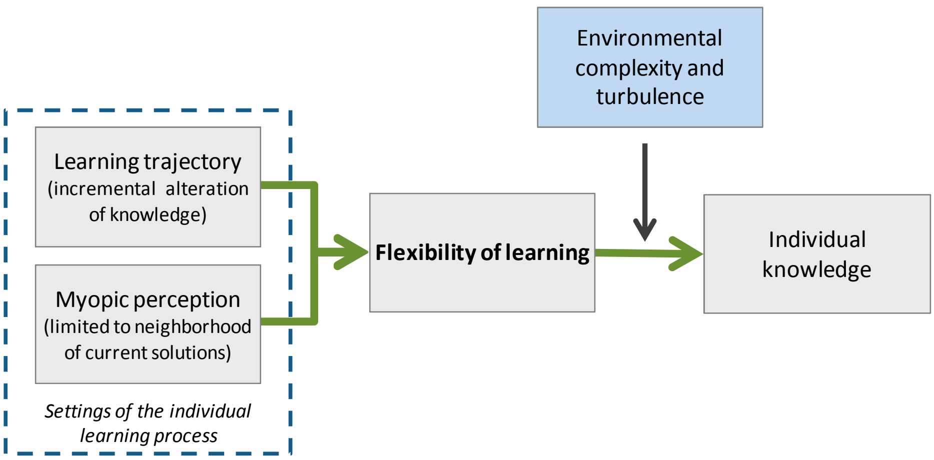

Figure 11: Dynamic of competence-enhancing learning

[134] Here again, please note the broad applicability of the NK approach. In general problem solving, local search heuristics are common problem solving strategies for efficiently tackling complex problems (Michalewicz & Fogel, 2004:42).

[135] Rivkin & Siggelkow (2002:33) in this respect claim that local search, or the climbing algorithms, are an appropriate approach to reflect boundedly rational decision making of a single individual trying to find a suitable representation for the complete landscape.

This, in a simplified way, directly points to the dynamic of individual learning in NK models. In the dynamic of competence-enhancing learning, the knowledge of the individual increases but her learning scope slowly deteriorates. As the individual moves across the problem landscape and improves her environmental representation, the number of better alternative representations in her close neighborhood decreases more and more until at last she ceases to learn. Kauffman & Levin (1987:26) had previously indicated that local search in NK landscapes has relevance for many optimization problems and point to the example of technological evolution. Consequently with relation to the space of possibilities the individual learning process leaves open, it tends to be *"'bushy' at the base, less bushy at higher levels, then becomes confined to single lineages that wend upward to local optima"* (Kauffman & Levin, 1987:26).

The mechanism of individual learning consequently is one of lowering the flexibility of future learning (Ackermann, 2003:243). In NK models, local search can be characterized as a process of diminishing learning possibilities which reflects that knowledge acquisition is subject to increasing returns. While improving her representation of the environment, the directions in which the learner can move within the NK space when taking the next step in learning, become increasingly limited. The better the learner's representation reflects the environmental state, the fewer moves which represent an improvement to her current representation are available.

Finally, if no better combinations are accessible, the search terminates. In this case, the learner has reached an optimum which often represents only the locally best combination. Nevertheless, the learner is unable to leave the locally best combination and reach the global optimum as a result of the aforementioned characteristics of the learning process. The learner is neither able to perceive the full scope of the landscape and identify the location of the optimum nor is she able to conduct large jumps in the landscape. In the incremental manner which the local search process implies, once the learner has locked in on a locally best solution, she is not capable of altering her position since she refrains from moving to representations which will deteriorate her result.

As implied in Figure 11, the dynamic of decreasing flexibility of individual learning or the enhancement of competence is moderated by the characteristics of the environment. As noted by Koch, Eisend, & Petermann (2009:71), *"[c]omplexity and bounded rationality are just two sides of the same coin."* The complexity of the learning task specifies the size of the gap between the individual's abilities and the environmental requirements concerning the individual's comprehension. In terms of the NK model, increasing complexity raises the number of local optima in the landscape and hence the probability for the agent to lock in to inferior solutions. Turbulence in the environment similarly impacts the difficulty of the learning task but from another direction. Environmental change leads to a redefinition of the learning task and hence requires ongoing adaptability on the side of agents.

In the subsequent chapter, we describe in detail the path-dependent characteristics of the competence-enhancing learning dynamic in NK models.

4.2.2 Individual Competence Enhancing Learning and Path Dependence in the NK Model

As we pointed out in the preceding chapter, the dynamics of individual learning processes can be suitably represented by the mechanism of local search in an NK framework. Likewise, we pointed out that the local search dynamic is one of lowering the flexibility of future learning. In the following, we explain how the characteristics of individual learning represented as local search in an NK landscape are related to path dependence phenomena and give some theoretical and model-guided implications for the importance of complexity as a contextual condition for path dependence to unfold.

In chapter 3.3, we pointed out that NK landscapes are general models of complex problems and dealt with their special characteristics which make them a useful approach for path dependence research. Here, we consider the process of how the agents approach the complex problem or, in other words, how they walk the NK landscape. This walk is described as a process of local search. It can be considered a path-dependent process since it shows the following characteristic features:

1) In contrast to purely mathematical descriptions of path-dependent processes,[136] the agent in an NK model experiences a historical contingency (Sydow, Schreyögg, & Koch, 2009:692-693). While the process is more open at the beginning, the learner is still imprinted from the past. In the NK landscape, this is reflected by their starting position. Learning individuals do not start from scratch but they already carry with themselves a reflection of the environment which, even if only partly, already impacts the direction their learning will take.[137]

2) Despite the historical contingency of the initial position in NK, it is the sequence of steps in the following learning process which finally determines where the learner ends up. From the learner's initial position, several local optima or possibly also the global optimum might be accessible and the final result depends on the way the learning process proceeds.[138] As already declared by David (1992:134), potentially path-dependent systems, have many stable attractors or, in other words, absorbing states to which the process will gravitate.

3) The basins of attraction around the different absorbing states in the NK landscape are the regions in which the learner is drawn to the local optimum. With respect to the learning process, this implies that the process is not eventless but that random events are able to push the learner into the domains of one of these asymptotic states (David, 1992:134; 2007:96). The events do not need to have a larger than normal impact but can be small and seemingly insignificant. In the learning process, the small events are the initial steps of the learner and it is their sequence which leads the learner to the critical juncture where she enters such a basin of attraction.

[136] See for example Arthur (1989) and Arthur, Ermoliev, & Kaniovski (1987).

[137] Levinthal (1997) uses local search adaptation in an NK model to show that the organizational form at founding has a lasting effect on its future.

[138] On hill climbing algorithms and their connection to local optima see Michalewicz & Fogel, (2004: 43-44). Please note that we do not use a steepest ascent hill climbing algorithm. As such the local optimum which is finally reached is not completely determined by the initial position of the agent. For the precise specification of the individual learning process, see chapter 5.3.

Figure 12, in a simplified way, illustrates the path-dependent nature of learning in an NK framework and shows how the learning process corresponds to the different phases of organizational path dependence (Sydow, Schreyögg, & Koch, 2009).[139]

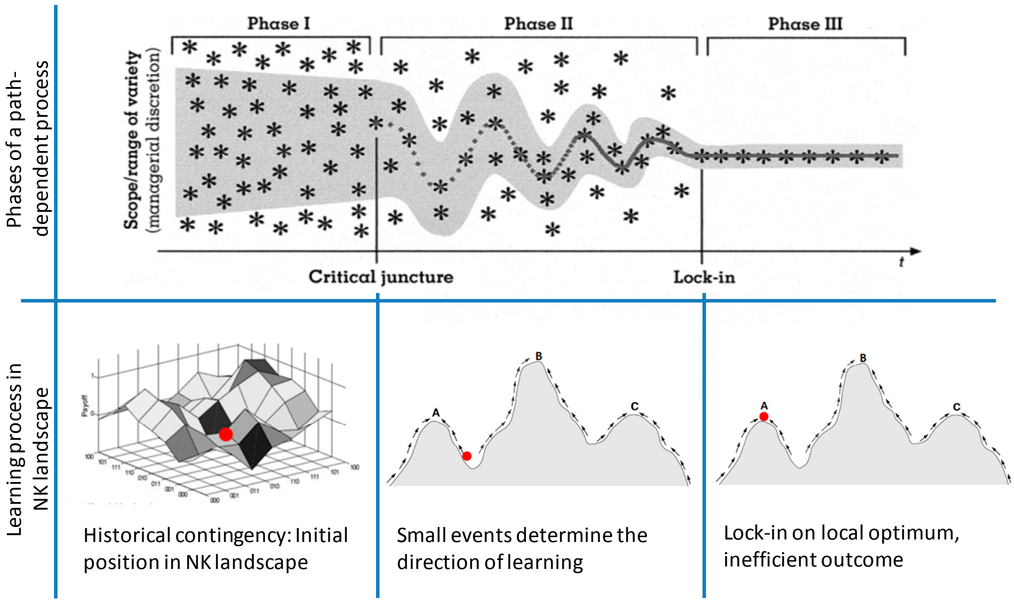

Figure 12: Learning in an NK landscape as a path-dependent process[140]

Individual learning as specified in this and the foregoing chapter, consequently, leads to a path-dependent outcome defined by David (2007:97) as *"a particular equilibrium among a number of potentially attainable limiting states."* The individual is not able to shake free from the history of past learning. While the history of the process accumulates, the probability that the process gravitates to different states decreases until in the lock-in it becomes zero. The lock-in is represented as a locally best solution for the complex problem imposed by the NK landscape. According to Siggelkow & Levinthal (2003:659), the local peaks in the landscape can be conceived

[139] See chapter 2.1.3 for the different phases of path-dependent processes.

[140] Illustration based on Ganco & Hoetker (2008:35) , Sydow, Schreyögg, & Koch (2009: 692), and http://en.wikipedia.org/w/index.php?title=Fitness_landscape&oldid=468190436. The pre-formation phase in NK is visualized with an overview of an NK landscape to capture the general structure of an NK landscape and the many possible starting positions for the learning agents. The landscape depicted here is of type $N = 6, K = 2$.

as competency traps. They are suboptimal results of learning which produces increasing returns to experience (Levitt & March, 1988:322-323).

Besides this dynamic of the process, the inefficiency of the lock-in is an important criterion for path-dependent processes. Simple problems can be characterized as having an easy to identify optimal solution. Egidi & Narduzzo (1997:682) suggest that mental overload significantly contributed to path-dependent learning results as the learner fails to deal with the whole space of strategies. Thus, opaqueness results from complexity. It is the complexity of the problem, the interdependence of several problem dimensions that causes local optima to emerge. Confronted with simple situations even the limited cognitive abilities of individuals suffice to identify the optimal solution. Consequently, with problems becoming simpler, inefficient learning results are less likely.

Competence-enhancing learning leads to path-dependent learning results for the individual. If we leave the social context of organizational learning out of the picture, the isolated learning processes of individuals would lead to highly divergent beliefs (Ackermann, 2003:244), at least in complex environments.[141] As also Denzau & North (1994:14-15) indicate, *"their mental models would tend to diverge (…) if there were not ongoing communication with other individuals of similar background"* as it is the case in organizational settings. Consequently, in an NK model, several agents each endowed with his own past experience, reflected in his initial position in the landscape, would follow separate learning trajectories and most likely develop different representations.[142]

In the following chapter, we go one step further and move from considering the isolated local search processes (as done in the preceding chapters) to interacting local search processes in NK landscapes. For this purpose, we build on the research approach of Jan W. Rivkin, Nicolaj Siggelkow, and Daniel A. Levinthal (Rivkin & Siggelkow, 2002; 2003; Siggelkow & Levinthal, 2003; 2005; Siggelkow & Rivkin, 2005; 2006; Rivkin & Siggelkow 2006; 2007) and see which implications can be derived for the path-dependent nature of search processes in an interaction of levels.

[141] See Levinthal (1997); here local search leads to the emergence of heterogeneity of organizational forms.

[142] We test this proposition in chapter 6.2.2.

4.2.3 Search Processes on Multiple Levels: Implications from Research on NK Landscapes

NK models have only recently gained prominence in organization research. Their application centers around the research approach of Jan W. Rivkin, Nicolaj Siggelkow, and Daniel A. Levinthal (Rivkin & Siggelkow, 2002; 2003; Siggelkow & Levinthal, 2003; 2005; Siggelkow & Rivkin, 2005; 2006; Rivkin & Siggelkow 2006; 2007) and focuses on formal structure and hierarchy.

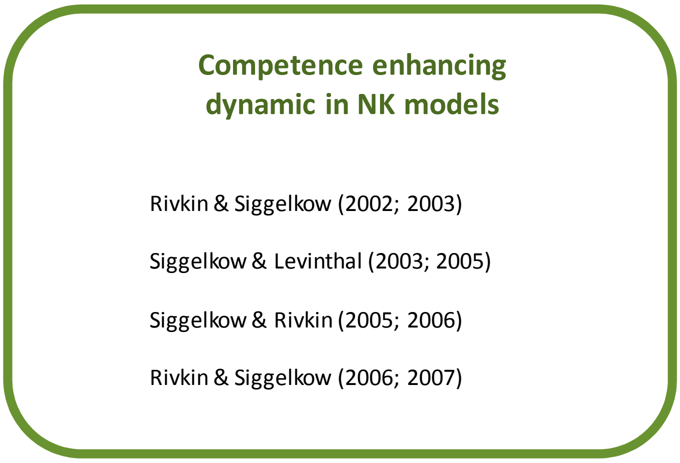

Figure 13: Computational models featuring the competence-enhancing dynamic

We can still derive useful conclusions for our research question not merely with respect to the configuration of the NK space in terms of complexity and turbulence[143] but also, if we distance ourselves from their focus on formal structure, from the interaction of processes on different organizational levels. Since the mutual learning dynamic is most of all an interaction of individual and organizational level and we consider modeling the organizational environment as an NK landscape (for which we already pointed out the reasons in close relation to its beneficial properties for path dependence research)[144] their research results become relevant for us. As already

[143] See on this aspect also chapter 4.3 where we consider the interplay of mutual and individual learning dynamics with respect to the environmental context.

[144] See chapter 3.3.

outlined in the chapter 4.1.3, mutual learning can be interpreted in terms of variation and selection. In the following section, we describe the dynamic in the aforementioned NK models based on the involved variation and selection processes so that their results become transferable to our research focus. Based on this outline, we can extract the properties which we assume to similarly encounter in our model.

In the Rivkin, Siggelkow, & Levinthal approach, the definition of features and parameters of interest does not directly focus on organizational learning but on the way decisions and authority are distributed in the organization. In accordance with the model's focus on organizational decision-making, the NK landscape here does not represent the organizational environment but stands for combinations of organizational decisions. However, the organization is viewed as a system searching for a good solution to a problem consisting of interdependent aspects.[145] The different characteristics of formal structure which the models investigate can be related to the way they influence the variation and selection dynamics of the search process.

The different formal structures are modeled by dividing the decisions in the organization between several decision-makers. Here, a central difference to a learning framework becomes obvious. While in organizational learning, the organizational members search for valid representations of the environment, thereby considering all dimensions of the problem landscape, in a decision-making framework, the search process represents the hierarchical decision structure of an organization; therefore, the department heads are confronted only with parts of the problem landscape[146] representing the decisions which are tackled by different decision makers (Siggelkow & Levinthal, 2005:91). For example, based on a total number of six decisions (which are equivalent to the six dimensions the NK landscape here encompasses), the first decision-maker determines decisions one to three, whereas decisions four to six are assigned to the second one (Siggelkow & Levinthal, 2003:654; 2005:91). All six

[145] Although in this approach the NK landscape does not explicitly represent the organizational environment, but combinations of organizational decisions, it still reflects something very similar. The organizational problem solving search implies an adaptation to the organizational environment which of course is the only reference frame to assess the performance of a chosen organizational strategy.

[146] For a similar approach in which the agents are only confronted with a limited number of dimensions of the NK problem landscape see for example Gavetti & Levinthal (2000) and Gavetti, Levinthal, & Rivkin (2005).

decisions taken together then define the performance of the organization or in other words its position in the NK landscape.

The decision-makers at the lower level, which in this approach are referred to as departments, are supplemented by a higher level coordinating body which we can think of as the top management or CEO. The organization thus encompasses two levels which interact. We can expect the decisions produced by the departments at the lower level to influence the results at the higher level of the organization. In contrast to models of learning, however, the upper level focuses on combining the different decisions of the lower level agents in order to determine the best complete solution for the organization.

As a result, these models deal with problems of modularity (Rivkin & Siggelkow, 2003:295). Even though the departments are supposed to search the problem landscape for the best decision, they do so only with respect to a limited number of problem dimensions which reflects their focus on departmental goals. It is the task of the upper level coordinating body to combine these modules to a solution valid for the whole organization. Consequently, compared to mutual-learning models, the Rivkin, Siggelkow, & Levinthal approach does not build on a dynamic of decreasing variety which is affected by fast and slow learning but on the characteristics of the walk of the agents through the landscape.[147]

The interaction between the two levels in the organization points to important characteristics of search processes in NK landscapes which involve multiple levels. Figure 14 provides a systematic overview of the Rivkin, Siggelkow, & Levinthal approach. For the unit and the aggregate level of the organization, the researchers inquire into several features which become clearer when attributed to either impacting the variation or the selection dynamics on the respective level.

[147] Dosi et al. (2011:3), in this respect, distinguish between two types of models. While in the first type the object of analysis is the cognitive division of labor in a problem-solving space, the other type addresses information processing and learning.

	Variation	Selection
Department level	Capability of department heads (ALTSUB)	Incentives (INCENT)
Aggregate level	Number of proposals of department heads (PROP)	Capability of CEO (ALTCEO)

Figure 14: Overview of the Rivkin, Siggelkow, & Levinthal research approach

Let us briefly consider the implications of each parameter. On the department level, the researchers affect the variation of decision alternatives by implementing a parameter related to the ability of the managers to assess decision changes (ALTSUB). A higher level of this parameter makes department heads smarter. They can change more than one decision in their decision combination and hence take into consideration more alternatives and the consequences of changing more than one decision element at a time. Concerning the selection process on the lower level, the incentive structures (INCENT) determine how the department managers rank the different alternatives that they are aware of. This parameter consequently determines which decision combinations are more likely to be forwarded to the upper level. The number of decision combinations which are then sent to the upper level (PROP) determines the upper level variation. The capability of the CEO in regard to his cognitive power (ALTCEO) determines how many decision combinations he selects to define the best possible option for the organization Rivkin & Siggelkow (2003:297-298).

By experimenting with the parameters, the researchers find that typically in the case of multi-level interaction, strategies should not be geared solely towards increasing variation or selection, but that increasing variation must be complemented by design elements which enhance selection processes. For example, in case of highly capable department managers, this feature should not be combined with a weak upper level management but with an active hierarchy which is able to guide the excessive search of the department managers (Rivkin & Siggelkow, 2003:300).[148] Clearly, the results are connected to the modular character of the search process on the lower level. To achieve positive outcomes for the aggregate organization, the CEO has to frame even intelligent search processes at the lower level since these tend to be focused on departmental goals. But besides their focus on modularity, the models of this approach point to the active behavior of the individual and organizational level from which important general characteristics of interacting search processes in NK frameworks result:

1) Variation in NK models must be understood as the possibility to explore a greater territory in the landscape and consequently as an opportunity to escape local optima. Increasing the variation on the lower level in terms of NK landscapes implies that the search of the agents is not bound to the immediate neighborhood of their current solution but that they are able to consider more distant solutions and as a consequence, instead of moving in a stepwise fashion, are even capable of performing jumps in the landscape.[149] For the single agent, this decreases the probability for lock-in. In terms of the aggregate or organizational level, variation refers to the number of solutions delivered by the individual level. In contrast to models of mere mutual learning, here these solutions have to be understood as points of departure for the active searches of the individuals.

2) The interaction between the process of variation at the lower level which is based on the agents actively searching the landscape and the selection process at the organizational level points to a property which is of particular relevance for analyses of path dependence. With regard to one level, search processes in NK landscapes have a strong tendency towards improvement and becoming locked in on a local optimum. In the interaction of levels, however, decision combinations of lower levels are able to dislodge the organizational level, here

[148] This conclusion is reflected in the articles of Rivkin & Siggelkow (2003) and Siggelkow & Rivkin (2005) as a simultaneous balancing of variation and stability brought about by organizational design elements. In the article of Siggelkow and Levinthal (2003) a sequential balance due to a change in the organizational structure helps to balance variation and stability.

[149] See for example Gavetti & Levinthal (2000).

> the CEO, from local optima whereas similarly decisions of the CEO are able to frame new search processes on the department level.[150]

While in mutual-learning models agents build on the variety of knowledge provided by the organization, in NK models, agents search the landscape actively. The active search process at the lower level complements the interaction between the levels and endows it with its own significant properties.

In the following chapter, we deal with the interaction between the dynamics of mutual and individual learning. Based on our knowledge of the different dynamics, we discuss how they might be affected by environmental complexity and turbulence. These assumptions subsequently guide our experiments with the model in chapter 6.

4.3 Considering the Interplay between the Dynamics of Mutual and Individual Learning in Complex and Turbulent Environments

So far, we have specified the mutual and individual learning processes in relation to already existing models. This step allows us to further detail our set of variables as outlined in chapter 2.4. With respect to our independent variables, we did not provide a specification of the variables which capture the settings of the organizational learning process or in other words how learning is framed by the context inside the organization.[151] In chapter 4.1.3.2, we concluded that most of the extensions of March’s (1991) model inquired into parameters which can be considered to simply moderate the speed of the involved learning processes. The speed variables in March’s (1991) model therefore seem to be able to capture the settings of the learning processes inside the organization in a fundamental way which is the reason why we employ them in our model.

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150 The difference in the retention dynamic is acknowledged by Rivkin & Siggelkow (2002) by introducing the notion of sticking points for all combinations of decisions from which the organization will not move. In their case of organizational decision-making, this might also imply that the sticking point is not a local optimum. This results from attributing different decisions to different departments. The department managers perceive only parts of the NK landscape and therefore select combinations which are not local optima. Moreover, the CEO sometimes might be able to introduce two changes at a time step if she has received two beneficial proposals from her managers. In this case, the agent representing the CEO does not proceed incrementally in NK but conducts a longer jump (Rivkin & Siggelkow, 2002).

151 See on the organizational context in the theoretical framework chapter 2.2.5.

Independent variables	Dependent variables
Complexity of environment	Learning success of code
Frequency of env. change	Average learning success of organizational members
Scope of env. Change	Knowledge heterogeneity
Speed of learning by the code	
Speed of learning from code	
Speed of individual learning	

Table 7: Overview of independent and dependent variables[152]

Dealing with the basic dynamics in both models - mutual learning and NK landscapes - allows us to speculate on the nature of the influence the environmental conditions exert on path dependence. Consequently, here we see Epstein's explanations (2008:1.9-1.12) on the reasons for modeling confirmed: Models illuminate the core dynamics of a phenomenon and help us to see basic connections. In the following section we consider the influence of the environmental context on the dynamics in path-dependent organizational learning.

4.3.1 Environmental Complexity

Sydow, Schreyögg, & Koch (2009) refer to the role of complexity as an enhancing context for organizational path dependence in the following way:

> *"Enhancing contexts—however important they may be—neither lead directly to path dependence nor represent a necessary or even sufficient condition for the occurrence of path dependence"* (Sydow, Schreyögg, & Koch, 2009:701)

With respect to environmental complexity, we may raise the question here, if this is true: Is complexity neither a necessary nor sufficient condition for organizational path dependence?

[152] The colors used to highlight the variables which specify the organizational settings indicate if they relate to learning at the individual level (green) or organizational level (orange). For a better orientation, variables of the environmental context throughout are highlighted in blue, dependent variables in yellow.

According to Dosi, Marengo, & Fagiolo (2003:64-65), path dependence in learning processes can have two drivers, mechanisms of social adaptation and complexity. Due to social adaptation, path dependence can occur even in simple environments. We encountered this mechanism in our discussion of mutual learning models, where path dependence shows in the homogeneity of beliefs brought about by social adaptation (March, 1991). Mutual learning in an environment without interaction effects (which create complexity in the first place)[153] hence can be considered to result in path-dependent outcomes. More interesting Dosi, Marengo, & Fagiolo (2003:64-65) find the forces which result from epistatic correlations which they claim can easily produce lock-in. In NK frameworks, these are modeled as problem complexity. The path-dependent nature of individual learning, excluding effects from social adaptation, results from an interaction between the learner's abilities and the complexity with which he is concerned. Due to the imposed connectivity between the different environmental dimensions, the problem for the learner becomes hard to unbundle. But of course the difficulty to figure out the best performing combination only holds if the learner is not perfectly rational but has limited cognitive abilities. Consequently, perfect rationality, similar to very simple learning tasks, makes path-dependent results unlikely. In simple environments which are not subject to interaction effects between their dimensions, individual learning leads to efficient outcomes. Problem complexity, therefore, can be identified as a necessary, though not necessarily sufficient, contextual condition for path dependence in *individual* learning but it only holds in close connection to the incremental way the individual learning process proceeds. Without complexity, even individual learning is sufficient to prevent path-dependent results. Consequently, we assume that environmental complexity is a necessary condition for organizational path dependence to occur but not a sufficient one. In more detail, this implies that without environmental complexity the organization would never become path-dependent (considering only the dynamics resulting from self-reinforcing organizational learning). Still, complex environments do not create path-dependent learning results every time. It may be possible even in complex environments that the organization succeeds to find an efficient learning result.

These assumptions are rather simple; they result from the dynamics we consider are inherent in path-dependent learning. If other self-reinforcing mechanisms such as

[153] See on the definition of complexity chapter 2.3.

complementarity effects or coordination effects act on the system, just as path dependence theory considers it to often be the case (Sydow, Schreyögg, & Koch, 2009:700), they have to be called into question. In this study, we can only test them for the workings of learning effects as specified in the foregoing chapters. The simple speculations above are made by considering the isolated effects of mutual learning or individual learning. But it is their interplay which makes learning organizational.

From research on NK landscapes, we derive implications for the system behavior under different degrees of complexity. NK landscapes allow problem complexity to be tuned, as a result, models using the NK approach always inquire into the effects of varying complexity. Here, researchers found system performance in search tasks to be strongly affected by the specified problem complexity (Levinthal, 1997; Gavetti & Levinthal, 2000; Rivkin & Siggelkow, 2002; 2003; Siggelkow & Levinthal, 2003; 2005; Siggelkow & Rivkin, 2005; 2006; Rivkin & Siggelkow 2006; 2007). For the learning system in our study, the question is to which degree path-dependent results become more likely with increasing complexity. This question directly relates to the intelligence of the organization. We pointed out in chapter 4.2.3 that the interaction of search processes acting on multiple levels is crucial for system performance. Each level can be considered to dislodge the other level from already attained local optima in the landscape.

This crucial effect has also been hinted at by the few models which can be considered to involve dynamics of mutual and individual learning in combination (Lazer & Friedman, 2007; Hanaki & Owan, 2010). But as these models do not focus on organizational path dependence, they have not dealt with this effect in more detail. In Figure 8, we outlined two models as being at the connection between the individual and mutual learning frameworks, and hence considering variation in systems of mutual learning or problem solving as added by the ability of the individuals to acquire new knowledge. Lazer & Friedman (2007:676) in their model of parallel problem solving indicate that knowledge exchange between individuals enables the individual to conduct jumps in the problem landscape which would not be possible otherwise in the mode of incremental search. This indication sheds light on the interaction between mutual and individual learning, at least at the individual level. Exchange with others does not only align the knowledge base (Ackermann, 2003:244),[154] it is also a mechanism of de-locking. Although Lazer & Friedman's (2007) model is concerned with the effect of different network structures and information distribution, if we abstract from this focus, we also derive two interesting aspects concerning the impact of complexity and turbulence to be tested in relation to path dependence. Lazer & Friedman (2007) argue that facing simple problems all network types are efficient, but besides this statement they do not inquire further into the effects of problem complexity. Still, this result works as another indicator that in simple environments path dependence is unlikely. Complexity here is a necessary condition to make distinctions between the different network types (Lazer & Friedman, 2007:682). Another result points to the importance of testing the impact of environmental change on systems which show a combined dynamic. We come to this aspect in the following chapter when we speculate on the effects of environmental turbulence.

Hanaki & Owan (2010) in their mutual learning model focus on organizational congruency which must be understood as a combined variable of socialization and individual learning. The combination of both processes prevents them from isolating the effects of mutual and individual learning in their model on which we build the interpretation of our simulation results. They find that organizations tend to bifurcate into either relying on individual search or socializing their members quickly. Somewhat contradicting to the established results in mutual learning models, a middle ground does not produce good performance. In models which feature mutual learning, however, it is often the middle ground, for example, a moderate degree of re-wiring in small world networks, which produces the best results. Hanaki & Owan's (2010) results seem to derive from another assumption in their model which changes the dynamic of mutual learning. Instead of adapting to the beliefs of the better performers, the updating of the code depends on the decision of the organizational members. Their results point us again to the central dynamic at work in systems of combined mutual and individual learning. The bad results of the middle ground in this model are due to the individual agents becoming stuck on local optima without being able to benefit from mutual learning. As they cannot agree on how to update their knowledge, the organizational performance (which in this case is assessed as the average individual performance) remains low. Although this again points us to the central dynamic of

[154] See on this aspect chapter 2.2.5.

alignment and de-locking in these models, we suspect that with a mutual learning process which resembles the original March (1991) model the model would show different results.

These explanations directly lead us to the heart of the mechanism's functioning. Mutual and individual learning dynamics have different effects depending on the level of the organization. Based on the knowledge acquired in this chapter, we can close the circle to our theoretical framework and relate the dynamics of mutual and individual learning to the twin concepts of exploitation and exploration.

	Individual level	**Organizational level**
Individual learning	Path dependent dynamic **Exploitation** Learning based on existing competencies	Increases internal belief variety **Exploration** Acquiring new knowledge about the environment
Mutual learning	Delocks from individual learning path **Exploration** Acquiring new knowledge from the organizational level	Path dependent dynamic **Exploitation** Sharing existing knowledge in the organization

Figure 15: The interplay of the basic dynamics of mutual and individual learning and their relation to exploitation and exploration[155]

We conclude that the effects of the dynamics of mutual and individual learning must be considered with reference to the level of the organization. In other words, if they contribute to exploitation or exploration depends on the level in the organization. Whereas in individual learning the organizational members merely exploit their competences in their specific area of expertise, for the organization, this process incorporates new knowledge on the organizational level and increases the belief variety. Consequently, with respect to the organizational level, individual learning

[155] Please note that throughout the figures in this dissertation we use similar colors to refer to the two feedback loops as described in the theoretical framework. Individual learning dynamics are highlighted in green, whereas the learning dynamics involving the organizational level are marked in orange.

contributes to exploration. On the other hand, in learning from the code the organization exploits already existing knowledge as learning from the code distributes the organizational knowledge set among the organizational members. But for the organizational members learning from the organizational level alters their knowledge state in a way which possibly makes new areas of expertise accessible. The individual through this learning process becomes able to leave his path of competence in the NK landscape. Therefore, what we consider to be exploitation on the organizational level incorporates aspects of exploration on the individual level and vice versa.[156] We assume that the interplay of individual and mutual learning significantly contributes to the intelligence of organizations and, as a result, enables them to tackle surprisingly complex problems and to keep path dependence at bay. In our experimental chapter,[157] we aim at deriving a deeper understanding of this interplay by varying the speed of the involved learning processes. By varying the speed of the learning processes, the mutual or the individual learning dynamic becomes more pronounced enabling us not only to inquire into the effects of complexity on the learning mechanism but also to get a better picture how the effects are brought about.

4.3.2 Environmental Turbulence

While complexity is a necessary condition for path dependence in individual learning but not for the mutual learning process or social adaptation, turbulence affects the organizational and the individual level alike. As the problem changes during the search task, the system has to follow a moving target which requires very different system abilities to arrive at a satisfying result compared to stable environments. In changing environments we assume that adaptability is rewarded. For adaptability, the organization depends on its sensors to the environment and on the variety of knowledge it commands. Although this indicates that exploitation in terms of a fast declining internal belief variety is problematic, it seems that in fast contexts fast aggregation and dissemination of knowledge becomes necessary for survival (Miller, Zhao, & Calantone, 2006:719). In their analysis of the benefits which can be derived

[156] On the transformation of exploitation in exploration and vice versa within and between organizations see Holmqvist (2004).

[157] See chapter 6.

from different formal organizational structures, Siggelkow & Rivkin (2005) come to the conclusion that when turbulence of the search task is introduced, the consequences of the variation and selection processes have different effects.[158] Siggelkow & Rivkin (2005:102) discover that for highly turbulent settings it is not so much the variation-inducing design elements that prove to be beneficial but that, in these settings, organizations have to boil down to efficient solutions speedily, thus selection processes should be emphasized. Kim & Rhee (2009) in their model of mutual learning similarly indicated that slow learning is not always beneficial as the organization in certain environmental conditions has only limited time for exploration. The effects of internal variety strongly depend on the scope and frequency of environmental change. The results of Lazer & Friedman (2007) detail this conclusion. Here, the optimality of the network configuration strongly depends on the timescale considered. Lazer & Friedman (2007) find that a faster exchange of information is beneficial when short run performance is considered while slower exchange shows good results with relation to long run performance. Consequently, system performance must be affected by the configuration of environmental change which determines the timescale available for the organization to learn about its environment.[159]

With respect to organizational path dependence, generally we assume that at least environmental change will not go unnoticed with the individuals acting as sensors of the organization to its environment. In accordance with Burgelman (2002:351-352), variation in the system will not die down completely since the changes in the environment are noticed by the organizational members. The point in question is more if the generated variety is able to keep up system adaptability. The variety generated by individual learning depends on the variety existing in the system. If the search of the individuals which is triggered by the environmental change starts from multiple positions, the organization explores a larger part of the landscape. Organizations which have already converged on a homogeneous mindset might notice the environmental change on the individual level but if and how much it impacts on the organizational level is unclear.

[158] See chapter 4.2.3 on the variation and selection processes in this research approach.

[159] Lazer & Friedman (2007:688-689) point out that incorporating environmental change in terms of its frequency and scope, is a worthwhile extension of their model.

In the following chapter, we describe our model of organizational learning which integrates individual learning and mutual learning between the organizational and individual level.

5 The Integrated Computational Model of Path-Dependent Organizational Learning

In the preceding chapters, we described which dynamics unfold in models of mutual learning as well as in models of individual learning in an NK framework. Both dynamics relate to different aspects of path dependence. While mutual learning causes a dynamic of decreasing variety, competence-enhancing learning when confronted with non-simple problems often terminates on local optima. Learning in both model types is depicted as a task which changes the way the learner perceives his environment. With respect to both model foci, the characteristics of the learner's environment have a strong influence on the outcome of the learning process. In our theoretical framework, we asserted that neither the individual side of learning nor its social side sufficiently explains organizational learning. Rather in organizational learning, the individuals acting as the sensors of the organization to its environment change their perceptions about it while being embedded in a context of communication and interaction.

Consistent with our theoretical framework, in the following section we bring together both learning processes, learning from direct experience which follows the individual learning trajectory (Ackermann, 2003:243) and learning from the experience of others as in the case of social adaptation, in an integrated model which will be used to inquire into the effects of environmental complexity and turbulence on the learning behavior of the organization. After giving a brief overview of our agent based model, in the subsequent chapters, we specify its elements and processes as is common in agent-based approaches using equations and rules (Harrison et al. 2007:1238). Furthermore, we transform the variables as defined in the preceding chapters into parameters for the simulation and consider how we diagnose path dependence with respect to the simulation parameters. As simulation models account for processes in (simulated) time, we also deal with the concept of time in our model and how it is related to real time.

5.1 Model Outline

Before we describe the components of our model in detail, we outline the models general functioning in order to provide an overview of its elements and processes and show how these interact.

Figure 16 illustrates that the three different types of elements in our model, the environment, the organizational code and the organizational members are connected by three different learning processes.

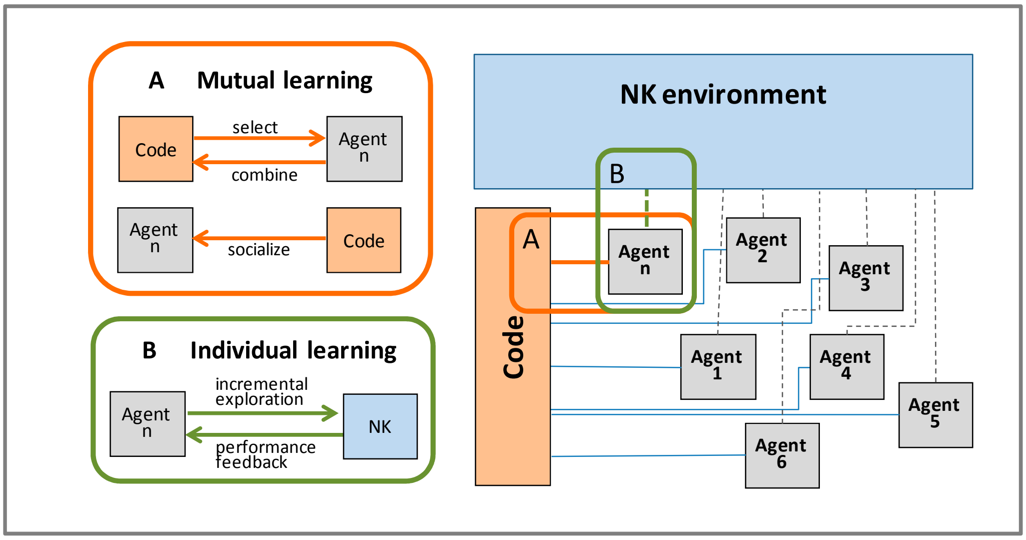

Figure 16: Processes of mutual (A) and individual learning (B) in the integrated model

Similar to March's (1991) specification, the organizational code is supposed to learn from the organizational members while these also take over knowledge held by the code. The organizational members, moreover, are also able to learn based on their individual experience which is described as an incremental search process in the NK landscape. The strength of all three learning processes can be influenced via parameters. These parameters simply define a probability that the agent, which can be either member or code, assimilates knowledge based on his experience or based on the organizational knowledge. In March (1991), these parameters were considered to define the speed or rate of learning and they will be referred to as such in the following. Consequently, a low rate of learning from the organizational code indicates that the individuals are only slowly socialized to the organizational belief system.

The different learning processes in our model interact. In learning from the organizational members, the code learns from the knowledge held by the better performing individuals and as a result improves the organizational representation of the environment. Simultaneously, the institutionalized memory represented by the code affects the knowledge state of the organizational members. The interaction of this socialization process and learning by the code leads to the described dynamic of decreasing variety of knowledge in the organization and also constitutes the basis for the organizational knowledge to improve.[160]

This classical interaction is extended by adding the individual learning process which is bound to counteract the dynamic of decreasing variety and therefore also to influence the selection process conducted by the code. By implementing individual learning as the above described myopic search behavior of the agents,[161] the selection dynamics at the population level, here the organizational level, is combined with an adaptive behavior on the individual level (Ganco & Hoetker, 2008:11). The selection process and the adaptive behavior of the individuals are based on feedback from the organizational environment. The code determines the better performing individuals on the basis of their knowledge about the environment; the individuals in their learning process increase their knowledge based on an evaluation of nearby options. Therefore, the dynamic in the model results from an interaction between the specified learning processes and the attributes of the organizational environment defined as an NK space. The parameters of the learning processes, the learning rates, determine the behavior of the agents whereas the parameters of the NK space, its complexity and turbulence, specify the organizational environment (Ganco & Hoetker, 2008:9). In the next two chapters, we specify the elements and processes in our model.

[160] On the dynamic of decreasing belief variety see chapters 4.1.1 and 4.1.2.

[161] On the dynamic of individual learning see chapters 4.2.1 and 4.2.2.

5.2 Elements of the Model

The computational model consists of three different elements which partly also reflect the class structure of the program code.[162] In the following, we formally account for these elements: the organizational environment, the organizational code, and the individuals in the organization.

5.2.1 The Organizational Environment

The organizational environment is described as a complex problem following the NK approach.[163] In an NK framework, a complex problem is defined as consisting of a number of dimensions which interact. Both the number of dimensions, described by the parameter N, and their interactions, described by the parameter K, can be defined according to the specification of the problem to be modeled.

The dimensions of the NK landscape are represented by a bit string consisting of N elements that either can have the value 0 or 1. Consequently, an NK landscape encompasses 2^N different combinations of elements in the bit string. Each of these combinations is associated with a performance score.

More formally, we define the environment as consisting of a set of dimensions $(x_1,\ x_2,\ x_3, \ldots, x_N,)$. Each dimension can take on S_i possible states, in our case $S_i \in [0; 1]$. Therefore, each point in the problem space is a binary string of length N.

The set of all points in the space or all possible configurations of the string is $S_1 \times S_2 \times S_3 \ldots \times S_N$. The performance of each of these binary strings (F) is defined as the mean of the performance contributions of its individual elements:

$$F = \frac{\sum_{i=1}^{N} f_i(x_i)}{N}$$

162 See Appendix B for the source code.

163 Concerning the roots of the NK approach in biology and its role in our model, see chapter 3.3. For its specification in the program code, see Appendix B, java classes NK_gen.java and NKSpace.java. We built our programming approach on Lazer & Friedman (2007).

The performance contribution of each element f_i is specified by randomly drawing it from a uniform distribution between 0 and 1 (Dosi et al., 2011:13-14; Lazer & Friedman, 2007:692).

N merely determines the size of the search problem whereas K defines how many dimensions affect the performance contribution of one dimension of the bit string. The interactions between the dimensions of the bit string significantly influence the difficulty of the search task as the performance contribution of one dimension is dependent on its own state and the state of K other dimensions, $f_i(x_i, x_i^1, x_i^2, x_i^3, \dots, x_i^N)$. The performance contribution of one dimension therefore can take on 2^{K+1} different performance values.

If, for example, element x_1 in the bit string is coupled with x_3, then a change of x_3 (e.g. from 0 to 1) will also affect the performance contribution of x_1. On the other hand in the case of a simple environment ($K = 0$), the performance contribution of one dimension is merely one of two set draws from the uniform distribution (Lazer & Friedman, 2007:692; Ganco & Hoetker, 2008:5; Dosi et al., 2011:13-14).[164]

Interactions between the dimensions of an NK landscape lead to the emergence of local optima which complicate the search for a good solution. In our case, the interdependencies between the dimensions are distributed randomly; they do not follow a specific pattern. For the program code, this means that in generating an NK space first the interactions are set randomly and then the performance values are distributed accordingly. For many systems, creating interaction patterns which reflect the interdependencies of the specific system is surely worthwhile. Rivkin & Siggelkow (2007) found out that the interaction pattern significantly influences the number of local optima of the problem landscape. As in our model, the NK landscape is supposed to reflect the organizational environment, we refrain from giving the interactions a specific pattern. Furthermore, in our analysis of variance (Lorscheid, Heine, & Meyer, 2011) in the experimental chapter we ensure that the influence of

[164] Two limit cases of complexity can be differentiated. If $K = 0$, the organization finds itself confronted with an environment of minimum complexity. Maximum complexity is reached if $K = N - 1$ (Ganco & Hoetker, 2009:5; Dosi et al., 2011:14). Maximum complexity results in a landscape in which a change in one element of the bit string leads to changes in the performance values of all other elements leaving the searching agents clueless where to look for a better combination.

random factors, from which the differing number of local optima in landscapes of similar complexity is one, is accounted for.[165]

5.2.2 The Organizational Level or the Code

As outlined in the preceding chapter, the distribution of performance values to all configurations specifies the problem landscape, which in our case represents the organizational environment. Generally speaking, NK approaches encompass two kinds of entities: complex problems or in other words the NK space, and agents. These agents can be thought of as algorithms, which search for the solution to the optimization problem (Gavetti & Levinthal, 2000:117). In this search task, the agents receive performance feedback from the environment for the position in the NK space they currently inhabit. Their position is represented by a bit string which is a combination of N elements which each either have the value 1 or 0. At every point in time the agents inhabit such a position in the NK landscape. The performance score of their positions is supposed to reflect how closely their representations match the real state of the environment represented by the global maximum in the problem space. Consequently, their current positions represent their knowledge state concerning the environment.

In our model, we have two different types of agents, the organizational code and the organizational members.[166] They differ from each other in two aspects: the way they are connected and their behavioral rules according to which the agents change their representations of the environment. With regard to its connections the code, representing the organizational belief system, has access to each organizational member.[167] It is via this organizational level that knowledge exchange in the organization takes place. The behavioral rules of the code reflect how the code aggregates the knowledge of the organizational members and will be dealt with in

165 See chapter 6.1.3.

166 In our simulation, we set agent 0 to represent the code whereas all other agents count as organizational members.

167 In the program, we work with a full network structure to provide this access, see java class netObj.java.

detail in the chapter on the learning processes in the model.[168] The code learns from the organizational members as it incorporates knowledge from the individual level in his representation of the environment. The representation that the code inhabits at every point in time reflects the belief the organization holds about its environment.

5.2.3 The Individual Level or the Organizational Members

The representations of all agents which are not the code reflect individual beliefs about the state of the external environment. All organizational members are confronted with the same complex problem represented by the NK landscape and potentially have the possibility to alter each dimension in their belief system. Therefore, we do not distribute the exploration of specific dimensions among the agents, such as, for example, in models which account for problems of modularity and the division of cognitive labor (Siggelkow & Levinthal; 2005; Siggelkow & Rivkin 2005; 2006; Dosi et al., 2011). The knowledge state of the organizational members, similar to the code, is characterized by their current position in NK and is reflected by a bit string of length N.[169] All organizational members are considered to learn according to the same rules, making use of two learning processes. They learn from the experience of others which is aggregated in the organizational code and they are able to conduct learning based on their own experience. In learning, the agents can be considered to walk the problem landscape.

The following example of a simple problem landscape provides a clearer picture of this essential connection between an agent's knowledge state and his position in NK. A simplified landscape which consists of three dimensions contains eight different binary strings. These eight different configurations of the bit string can be visualized as corresponding to the different vertices of a cube.

[168] See chapter 5.3 for a detailed description of the learning processes and the pseudo code.

[169] Besides their knowledge state, the organizational members are not endowed with other characteristics. Additional characteristics of the organizational members can be considered a sensible extension to the model, for more information see chapter 7.3.

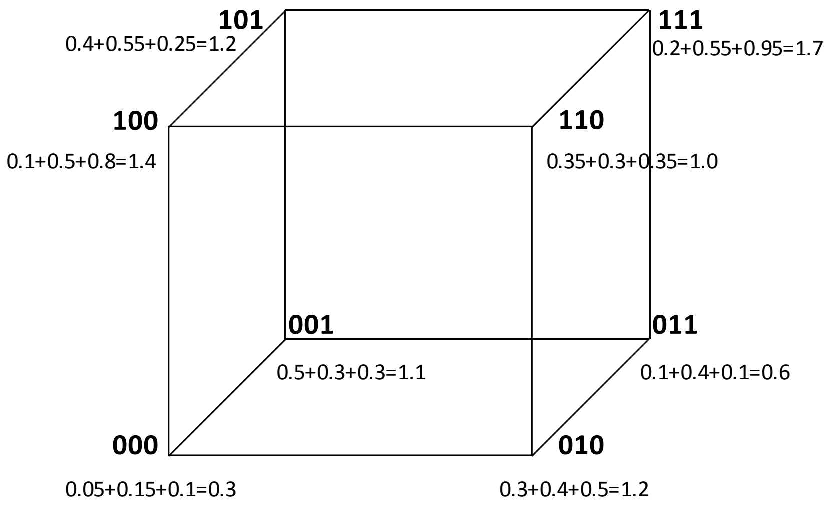

Figure 17: Example of a problem landscape with N=3 and K=2, represented on a cube
(Source: Siggelkow & Levinthal, 2005:93, slightly adapted)

Imagine an agent to be located in the point configured as [0,0,0]. By proceeding incrementally, which here means altering only one bit at a time, the positions [1,0,0], [0,0,1] and [0,1,0] are accessible. In a learning process based merely on myopic search, these neighboring positions on the cube would be the ones which are feasible for the agent. To choose a new position, the agent relies on the feedback which he receives from the NK environment. In Figure 17, the performance values are displayed below every binary string. They consist of three values which depict the draw from the uniform distribution for the corresponding bit in combination with its interacting bits.[170] Thus, every agent at every time point in the simulation holds a specific position in the NK landscape which corresponds to a specific bit string with its associated performance value.

In the following chapter, we specify the learning processes in the model which correspond to the way the agents, referring to the code and the organizational members move in the NK landscape.

[170] K in this simple landscape equals 2 which here represents full interdependence. Every value for every bit therefore is a new draw from the uniform distribution over the unit interval (Siggelkow & Levinthal, 2005:92).

5.3 Learning Processes in the Model

The model encompasses three learning processes. First, the code learns from the knowledge of the organizational members. Second, the organizational members are socialized to the beliefs of the organization. This exchange constitutes mutual learning of organizational and individual level as the code shapes the beliefs of the organizational members and in turn is shaped by them (Miller, Zhao, & Calantone, 2006:709). Mutual learning thus has evolutionary aspects because successful beliefs are selected for transfer inside the organization (Rodan, 2005:414-415). Simultaneously, the internal knowledge variety in the organization is reduced. As well as learning from the code, the individuals in a third learning process are able to acquire new knowledge about the organizational environment. This learning process proceeds incrementally as it is based on the experience of the organizational members. Generally, the knowledge acquisition of the members introduces new knowledge into the organization; hence it increases the internal knowledge variety. In the following section, we consider each of the learning processes in turn. The learning processes are formalized by using behavioral rules for the agents (Harrison et al. 2007:1238). We conclude this chapter with an overview of the behavioral rules in the sequence in which they are enacted by the agents.

5.3.1 Learning by the Code

First, we consider how the code learns from the organizational members. Learning by the code proceeds in two steps. For learning by the code to show evolutionary aspects or in other words, to lead the organization to a better representation of its environment, it has to involve a kind of selection process. As a first step, therefore the code identifies the better performing organizational members and, from their environmental representations, generates a majority view on each environmental dimension. In the next step, the configuration of a specific dimension from this majority view is transmitted to the code according to a defined probability. In our model, this probability is referred to as the speed or rate of learning by the code or (p_c).[171]

[171] In March (1991), the speed of learning by the code is reflected by parameter p_2.

The two general steps involved in learning by the code have been configured differently in models of mutual learning. Differences can be identified with respect to the configuration of the rate of learning or in the way the group of better performers is identified.

In March (1991:74), learning by the code is conducted as the code learns from all members who perform better than the code itself. Furthermore, the different solutions are weighted according to how often they appear in the superior group. Thus, for every environmental dimension it is counted how often the better performers consider it to be 0 or 1. If numerous agents in the superior group assert that the concerned dimension has a specific value, this raises the probability that the specific value for this dimension will be incorporated into the code's representation.[172] In March's (1991) model, the probability is therefore a function of the size of the group of the superior performers.

Most recent models of mutual learning follow a slightly different approach with respect to the rate of learning. The models consider it to be independent and not weighted according to the distribution of the majority view in the group of better performers (Miller, Zhao, & Calantone, 2006; Kim & Rhee, 2009; Fang, Lee, & Schilling, 2010). Rodan (2005) changes the way the group of better performers is identified.[173] He argues that the size of the group of better performers influences the learning process.

For our model, we were therefore obliged to test several versions of the process with which the code learns from the organizational members. With regard to the rate of learning, we tested the logic of March (1991) with a weighted probability[174] and the non-weighted probability of later versions. We also inquired into the effects of altering the size of the group of better performing organizational members that the code identifies for learning. In our experiments we deal with the logic employed by March (1991) and an extension in which the size of the superior group can be adapted. In the

[172] In our simulations, we refer to this configuration as the 'March logic' of learning by the code.

[173] Rodan (2005) introduces a stringency parameter to influence the size of the superior group.

[174] In this case a dimension of the code stays unchanged with probability $(1 - p_c)^k$ where k is the difference between the number of better performers with the majority view on a specific dimension and the better performers with the minority view. In the experimental chapter, we refer to this logic as March weighted.

overview (pseudo code), at the end of the chapter on the learning processes, we refer to the latter version.[175]

5.3.2 Learning from the Code

In every time step of the simulation, the code knowledge also impacts on the individual members. As the code represents the organizational belief system, individuals alter their beliefs continuously as a consequence of socialization into organizational norms and consequently adapt their knowledge state to that of the code (March, 1991:74). This socialization process is not supposed to involve performance assessments conducted by the individual members.[176] Rather, the n-dimensional set of beliefs which is promoted by the organization shapes the beliefs of the individuals unaffected from efficiency requirements in relation to the organizational environment. Learning from the code therefore involves no selection process on behalf of the organizational members. These simply refer to the representation of the organizational knowledge as represented by the bit string of the code and incorporate every bit into their individual representation of the environment with a defined probability. Consequently, even if the code is likely to have a better representation of the environment as the average organizational member, learning from the code can reduce the knowledge of particular individuals. Similar to March (1991), we refer to the probability with which the agents in the organization learn from the code as speed or rate of learning or simply as (p_a).[177]

5.3.3 Individual Learning

The third learning process is concerned with experiential learning of the organizational members. As outlined before, the process is subject to restraints.

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[175] See Figure 18.

[176] Socialization is considered to happen unconsciously. Efficiency of the transmitted norms mostly is not thought to be a relevant criterion. Rather beliefs in socialization are transmitted because they reflect a majority view in the organization or are enforced through incentives, see for example March (1991), Rodan (2005), Miller, Zhao, & Calantone (2006).

[177] In March (1991), the speed of learning from the code is determined by parameter p_1.

Individuals are only able to alter their existing knowledge incrementally, and they have only limited oversight over the problem landscape. These restraints are reflected in the local search process conducted by the individual agents in the NK landscape.

The individual learning process proceeds in two steps. According to the local search algorithm, the agents[178] in a first step randomly consider altering one bit of their current n-dimensional environmental representation. With reference to the previous example of a basic problem landscape depicted as a cube,[179] agents are only able to assess bit combinations which are direct neighbors of their current position. From their current vertex on the cube they therefore choose at random a directly connected vertex for assessment. For the one bit alteration, the agents receive a performance feedback from the NK landscape. If altering the bit improves their environmental representation the agents implement the change in a second step. If the alteration has no positive effect on their performance, the agents randomly try another bit. As a result, the agents continue to search for a better representation until they have reached a local optimum. In this case, they are unable to improve their current representation by altering just one bit of their bit string.[180] The speed or rate of individual learning, similar to the other learning processes, is defined by a probability (p_{expl}) which determines the likelihood that individual agents engage in local search behavior.

Figure 18 provides an overview of the three learning processes and outlines the sequence in which they are enacted by the agents. Illustrations of this type are referred to as pseudo code since they describe the model in terms of its rules which are later transferred into program code. The pseudo code therefore describes a complete run of the model from its initiation to the end.[181] The three learning processes are enacted in the steps 3.b.) to 3.d.). We see here that individual learning and learning from the code

[178] Except the organizational code which is not supposed to learn experientially.

[179] See Figure 17 in chapter 5.2.1.

[180] Please note, that we do not employ a greedy search algorithm in which case the individuals would search their neighborhood in NK for the best solution and take on this belief-set. In classical local search, they merely search for an improvement compared to their current position which must not be the best point which is available by altering one bit of their bit string. For a given landscape and location of the agent, a greedy search in an NK landscape without employing any other leaning processes can be determined in advance which would also conflict the requirements of path dependence theory.

[181] In the experiment, the model is run repeatedly. The number of required runs is determined according to the analysis of variance to generate meaningful and comparable results for the different parameter configurations, see chapter 6.1.3 and Appendix D.

are processes conducted by the organizational members whereas learning by the code is the single process initiated for the code which in the pseudo code is referred to as agent 0. A model, in consequence, can be considered as a series of interlinking processes which are embedded in a loop so that for each agent, the relevant processes are repeated in each time step (Carley, 1992:41).

```
1.  Set parameters and give a random seed
2.  Load NK space
    Create agents and their connections according to specification of organization
3.  For 0 ≤ tick < 1000
    a.)  check if landscape must be altered (frequency of change x)
         if yes: alter landscape according to τ (scope of change)
         update performance of agents
    b.)  for each agent 1 ≤ i < pop
         i.   explore with prob. p_expl:
                 choose random one bit from n-dimensional representation
                 test change of bit
                 if performance increases: alter bit and stop, otherwise repeat with new bit
         ii.  update performance of agents
    c.)  for code
         i.   learn from individuals with prob. p_c:
                 select better performers and ceate most common bit array
                 learn every bit with prob. p_c
         ii.  update performance of code
    d.)  for each agent 1 ≤ i < pop
         i.   socialized with prob. p_a:
                 learn every bit from bit string with prob. p_a
         ii.  update performance of agents
    e.)  back to a.)
```

Figure 18: Pseudo code of model run

We notice that before the learning processes are triggered several important steps with relation to the configuration of the organizational environment take place: As a first step, the landscape is created according to the specified problem complexity. For every time step then the learning processes are initiated for every agent according to type (member or code). Similarly for every time step the model controls if the environment has to be changed. The environmental change is specified by two parameters referring to the frequency and scope of change. In the following chapter, we explain which parameters are used in the model and how these relate to our variables as specified in foregoing chapters.

5.4 Classification of Model Variables

Whereas the independent variables guide the behavior of the model and determine the experimental settings, the state of the simulated organization in each time step is described by the dependent variables. Beside these two obvious categories of variables, simulation models encompass a third category: the control variables. Control variables are close to independent variables because they could also influence the model behavior but generally are not important for the research question. It is a decisive advantage of simulation models that all variables, even the ones which are not central for the research question at hand, can easily be named and made transparent.[182] This is also what we aim to do in this chapter. We describe how independent and dependent variables in the model are configured and outline which additional variables 'hide' in the model and how we account for their influence on model behavior (Lorscheid, Meyer, & Heine 2011:12). We also relate the variables to the parameters which represent them in the program code.

Table 8 shows the classification of the variables in our model as well as the names of the respective parameters in the program code. In the following we define the variables in the three categories starting with the dependent variables.

[182] As all variables are contained in the program code and have to be specified accordingly, construct validity in simulation research can be considered high (Davis, Eisenhardt, & Bingham, 2007:490). See on this also chapter 7.1 concerning the validity of the model.

Dependent variables	Parameter name in simulation
Learning success of code	codeScore
Average learning success of organizational members	avgScoresRaw
Variety of beliefs	heterogeneity
Number of unique beliefs	uniqueAgents

Independent variables	Parameter name in simulation
Complexity of environment	K
Frequency of env. change	x
Scope of env. Change	τ
Speed of learning by the code	probabilityCode
Speed of learning from code	probabilityAgents
Speed of individual learning	probabilityExplore

Control variables	Parameter name in simulation
Number of ticks	ticks
Number of runs	runs
Number of agents	pop
Size of superior group, elite size (number of agents code accesses for learning)	numBetterPerf
Number of env. dimensions	N
Keep or abolish dependencies of env. dimensions on change	keepDependenciesOnChange

Table 8: Classification of variables and respective parameter names[183]

5.4.1 Dependent Variables

The model produces output concerning two general categories, the learning success of the organizational system and its knowledge variety. In the overview, we see that both of these output categories are divided into two separate variables which allow us to better assess the dynamics in the model. In the following section, we deal first with the

183 For a complete overview of java classes, parameters and variables extracted from the program code to increase the model transparency (Lorscheid, Heine, & Meyer, 2011:10), see Appendix A.

variables describing the learning success of the system and after that with the variables which account for its knowledge heterogeneity.

Learning Success

The learning task of the organization consists in finding the most fitting representation of the organizational environment. This corresponds to the maximum score in the NK landscape or its global optimum. Therefore, the learning success reflects how well the organization has learned. In defining the learning success, two aspects are of special importance: First, the learning success of the organization can be interpreted in terms of the score reached by the organizational code or as the average learning success which is reached by the individuals in the organization. The second aspect concerns the absolute or relative value of the learning success.

For every time step, the simulation reports the learning success of the organizational code (*codeScore*) and the average learning success of the organizational members (*avgScoresRaw*). In the simulation, agent 0 takes on the role of the organizational code, and thus the learning success of the organizational level can be extracted by simply plotting the learning success of agent 0 in each time step after it conducted the learning processes as defined for the code.[184] The average learning success of the organizational members is simply the average performance score of all agents who are not the code in each time step, after conducting the learning processes as defined for the organizational members. There is one major advantage in considering both performance values. They allow conclusions with respect to the process of knowledge convergence in the organization. If the model converges on one solution, in the end, the learning success of the code and the average learning success of all individuals will have an equal value. As long as different solutions are present in the organization, the two scores will deviate.

Typically, neither the learning success of the code nor the average learning success is defined as an absolute value but as relative to the maximum score in the NK landscape. If the organization succeeded in finding the best solution in the NK landscape, then its learning success would be 1.0. Every other score reached by the

[184] See chapter 5.3 on the learning processes in the model.

organization can be interpreted as a percentage of the global maximum in the defined landscape. The relative score, consequently, expresses the ratio of the performance score reached by the organization to the performance it would have acquired if it had learned the best solution. Referring to the relative learning success therefore contains information on whether the agent has reached the best solution possible or how far he missed the global peak (Ganco & Hoetker, 2008:12-13). Despite these obvious advantages, reporting the relative performance is only valid if agents from different settings (e.g. different complexities) do not interact and if K is not endogenized (Ganco & Hoetker, 2008:13).[185] Furthermore, we found that using the relative score is not recommendable in changing environments as these experience a regression to the mean of the global optimum which as a result gives a false impression of the development of the relative organizational performance. When we inquire into the effects of environmental turbulence, we therefore report on the absolute learning success of the organization.[186]

Dealing with environmental turbulence also brings up another question in relation to reporting the learning success of the organization. The learning success is determined in each time step of the simulation. If we consider that knowledge of the organization eventually becomes obsolete due to a changing environment, it not only matters how well an organization learns but also how fast (Ganco & Hoetker, 2008:17-18). In a stable environment without considering competition between several organizations, measuring the performance of the organization upon convergence of all beliefs might be sufficient. In a turbulent environment however, we also should consider temporary and average performance across the environmental cycles to get a more appropriate assessment of the organizational learning success.[187]

Knowledge Variety

The other main output category in our model refers to the variety of knowledge in the organization. Similar to the learning success of the organization, we have two

[185] See on this also Ganco & Hoetker (2008, figure 3) which compares absolute and relative performance for different landscape types and Appendix H.

[186] See chapter 6.4 for the experiments with environmental turbulence.

[187] See also chapter 6.4 on this aspect.

variables which shed light on the different aspects of knowledge heterogeneity. First, we report the number of different solutions in the organization present in each time step (*uniqueAgents*). If the beliefs of two organizational members represented by bit strings differ in one dimension or more they are considered to represent different knowledge states.

But this parameter does not involve any assessment as to what extent the two solutions differ. Therefore we integrated a second parameter which enables us to assess the diversity of knowledge in the organization not only according to the number of different beliefs present in the system but also in the light of how diverse these are.[188] Similar to Fang, Lee, & Schilling (2010), this heterogeneity parameter is constructed by conducting pair wise comparisons of all individual beliefs in the organization.

There are $\frac{1}{2}k\ (k-1)$ pairs of individuals in the organization with $k = pop - 1$ (the number of organizational agents in the system (pop) without the code, represented as agent 0). For each pair of individuals, N dimensions of the bit string have to be compared. The heterogeneity in the organization then is determined as follows:

$$Heterogeneity = \frac{2}{N\ k\ (k-1)} \sum_{i=1}^{\frac{1}{2k(k-1)}} \sum_{j=1}^{N} \omega_{ij}$$

Here, ω_{ij} is considered to be 1, if the beliefs of the i^{th} pair of individuals in the j^{th} dimension are dissimilar and 0 if they are the same.

The two described parameters, the number of different solutions in the organization and their heterogeneity allow us to monitor the development of knowledge variety in the organization.

5.4.2 Independent Variables

The independent variables reflect which different organizational settings can be explored in the simulation. In our case in the simulation experiments, we inquire into effects of environmental complexity and turbulence in different learning conditions.

188 In Fang, Lee, & Schilling (2010:632,) the parameter is called dissimilarity index.

Our independent variables in our model therefore reflect variables which describe environmental complexity and turbulence to configure the environment and variables of learning speed which we use to specify the learning conditions inside the organization similar to March (1991) in order to modulate the two dynamics of individual and mutual learning.

Environmental Complexity

In chapter 2.3, we defined the environmental characteristics complexity and turbulence. Environmental complexity is determined by the number of different dimensions the organization has to deal with and how strongly these dimensions interact with each other.

The organizational environment in the simulation is defined as an NK landscape for which we can vary the parameters N, the number of dimensions that the landscape encompasses[189], and K, the number of interactions between these dimensions. Whereas K is a measure of how many other dimensions affect the performance contribution of one dimension, the number of possible performance values in the landscape (2^N) stays the same independent of K, it is only determined by N. As NK defines a limited problem space, searching this space for the optimal solution is sensitive to the number of agents who search within it. Even a vast problem space can be explored more fully, if many agents are involved in the search. Therefore, as is common when working with NK models (e.g. Lazer & Friedman, 2007; Siggelkow& Rivkin, 2005), we have to align the number of learning agents and the size of the problem space.[190] In configuring the model, we therefore determine N and the number of agents (pop) so as to impose a reasonably large search space on the organization. In this search space of defined size, we then influence the difficulty of the learning task by manipulating the parameter K. Finding the single optimum in a simple environment (as in the case of $K = 0$) should be feasible for the agents even when employing only plain incremental learning. It is the presence of local optima which emerge when $K > 0$ which complicate the learning task. Whereas N specifies the size

[189] Or, in other words, the number of elements in the bit string which represents the beliefs of each agent.

[190] See chapter 6.1.2, the configuration of the model for the determination of N and pop.

of the search space and will be fixed in the configuration of the model, it is K with which we will vary the complexity the organization faces.

Environmental Turbulence: Frequency and Scope of Environmental Change

The second environmental characteristic whose effects we wish to investigate is environmental turbulence. Environmental turbulence is here considered to vary according to its frequency and scope (Kim & Rhee, 2009). In our experiments on environmental turbulence we therefore vary how often the NK landscape is disturbed and how strong these disturbances affect the landscape. Similar to Siggelkow & Rivkin (2005:104), the environment experiences shocks of comparable scope in periodic intervals. The frequency of environmental change is reflected by the parameter x which simply represents the interval in which landscape changes are repeated. As outlined in the pseudo code in Figure 18, in every time step of the simulation the program evaluates if a change is due and initiates it accordingly.

The scope of environmental change is reflected by parameter τ which can take on values between 0 and 1. Therefore, during a model run in a turbulent environment, the landscape is altered every x ticks. The magnitude of these changes is defined by redrawing the performance contribution for each dimension as follows:

$$f_i = \tau * f_i + (1 - \tau) * u$$

where u is a new draw from the uniform distribution.

Consequently, the parameter τ defines to what degree the past and future performance values of the NK landscape are correlated.

Changes of high scope which, as can be concluded from the foregoing paragraph, correspond to changes with low τ are bound to redefine large parts of the performance score of the different solutions offered in the NK landscape and, consequently, strongly devaluate the knowledge acquired by the agents. In an extreme case, where $\tau = 0$, there is no correlation between past and future performance values (Siggelkow & Rivkin, 2005:104-105).

Learning Speed

Besides the independent variables causing the organizational environment to vary, the three different learning processes in our model (learning *from* and *by* the code and learning based on individual experience), can also be influenced by probability parameters. These parameters (p_a, p_c, p_{expl}) affect with what probability the agents change their belief representations during a learning task. A high probability therefore indicates that learning progresses quickly. In case of a high p_a or a high p_{expl}, the organizational members learn rapidly from the code or from the organizational environment, in case of a high p_c, the code learns quickly from the individuals in the organization. With a low probability, on the other hand, it is not very likely that the agents alter their belief representations in each time step. In this case, learning progresses slowly.

In the model, the probability parameters are employed in the following way. In learning *from* the code, the organizational members orientate towards the belief-set of the code (the code's bit string). If their belief-set in any dimension differs from that of the code, a random number between 0 and 1 is drawn. If this random number is below p_a, the organizational member takes on the belief of the code for the concerned dimension. Every organizational member repeats this process for every dimension that his belief-set differs from that of the code.

Learning *by* the code proceeds in a similar way. The code takes the belief-set of the better performers in the organization[191] and for each dimension that its beliefs differ from that of the better performers, a random number is drawn. If the random number is below p_c, the code incorporates the belief of the better performers into his belief-set.

In individual learning, p_{expl} determines how learning progresses. This parameter determines with what probability the individuals conduct local search in NK. Here, a random number is drawn and if it happens to be below p_{expl}, the members of the organization randomly alter one dimension of their belief-set. They only incorporate the altered dimension into their belief-set if they receive a positive feedback from the

191 See chapter 5.3 on the learning processes where we explain how the better performers and their belief-set is determined.

environment, or in other words, if the new combination of bits provides a better performance than their former one. Thus, p_{expl} determines how fast the organizational members explore their neighborhood in the NK landscape.

5.4.3 Control Variables

In the classification of variables,[192] we also specified a number of control variables. Most of them are what usually falls into this category in simulation research: The number of time steps ($ticks$), how often the model is repeated ($runs$), the number of agents (pop), and for NK models also the number of dimensions of the problem landscape (N) are parameters which commonly are specified in the configuration of the model ahead of the simulation experiments.[193]

Two other control variables are mentioned in the classification of variables. They are not central to our research question but they do have an effect on the simulation outcome. One determines whether in the case of environmental turbulence, it is not only the performance values of the different configurations in the NK landscape that are redefined but if the interactions between the environmental dimensions are set anew ($keepDependenciesOnChange$). This parameter further complicates learning in a changing environment.

The other variable is a result of working with the model. In chapter 5.3.1, we explained that different algorithms can be applied for simulating learning *by* the code. March (1991) determined the superior performers in the organization as all members that perform better than the code. We work with his configuration but for reasons to be explained in detail in chapter 6.3 also introduced a parameter for setting the size of the superior group ($numBetterPerf$). As recommended by Lorscheid, Heine, & Meyer (2011:10), in the first experiments we included this parameter to understand its effects and give it a plausible specification.[194]

[192] See Table 8.

[193] See chapter 6.1.

[194] See chapter 6.3, experiments in a complex environment and Appendix G.

To conclude, our model consists of six independent variables which are supposed to determine four dependent variables. Figure 19 shows to which elements and processes in the model the variables are connected.

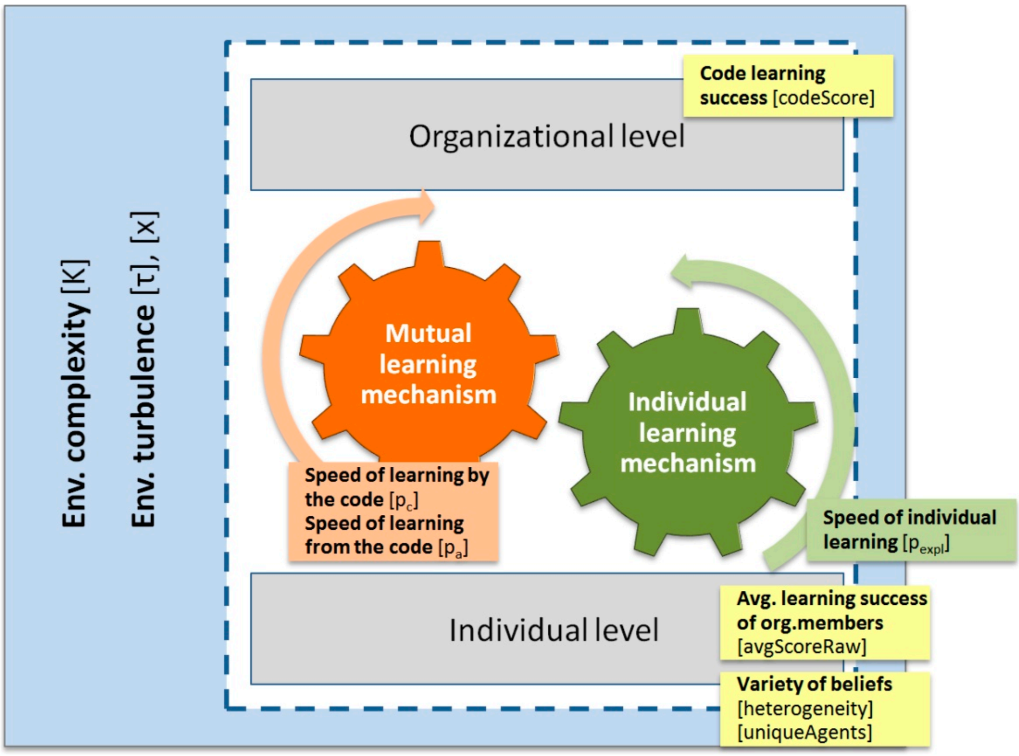


Figure 19: The integrated model and its variables

The independent variables either affect the organizational environment or the learning processes in the organization. With the rates of the learning processes, we can vary how pronounced the different learning processes are and therefore directly influence the interaction between the mechanisms of mutual and individual learning which is at the heart of our model. As explained in chapter 4.3, this interaction is supposed to determine the adaptability of the organization and hence its propensity for path dependence in different environmental circumstances. The focus of our inquiry is on the environmental variables of complexity and turbulence.

5.5 Specifying Path Dependence in the Model

While in the preceding chapter we explained the dependent variables of our model, we did not explicitly clarify their relation to organizational path dependence. In chapter 4.1.2 and 4.2.2, we connected the dynamics of the processes of mutual learning and competence-enhancing learning to organizational path dependence. In the following section, we define path dependence in our model in terms of the specified variables.

In the development of an organizational path three different stages can be distinguished: the pre-formation, the formation, and the lock-in phase. The imprinted contingency of the pre-formation phase still offers abundant room for the organization to maneuver which then becomes more and more constrained during the formation phase. In this stage, the core pattern which represents the organizational path becomes increasingly visible (Sydow, Schreyögg, & Koch, 2009:692-696). In our model, this corresponds to the following development. Initially starting from a random distribution of beliefs in the organization representing the imprinted contingency of the pre-formation phase, the variety of beliefs in the organization decreases and ever more restricts the possibilities of the organization to explore different parts of the problem space. As the different beliefs in the organization are molded into a common mindset and alternative beliefs are crowded out, the adaptability of the organization declines and it becomes locked to a specific area of the NK landscape.[195] With relation to the model's dependent variables, the presence of only one belief-set in the organization or a low number of belief-sets with low variety [low $uniqueAgents$, low $heterogeneity$] would indicate that the organization has reached a homogenous mindset.

The diagnosis of organizational path dependence requires that this mindset is inflexible and at least potentially inefficient (Sydow, Schreyögg, & Koch, 2009:694-695). Both criteria are connected to the notion of a local optimum. With respect to the inflexibility criterion, if the organization has not reached a local optimum, the individuals in the organization continue to explore their neighborhood as they are able

[195] Castaldi, Dosi (2004:21) consider the building blocks of path dependence to be increasing returns in knowledge accumulation, boundedly rational actors, collective selection mechanisms and the social embeddedness of the adaptation and learning process.

to learn based on their own experience. Still, a declining variety of beliefs in the organization limits their ability to explore other areas of the problem landscape by exchanging knowledge with their colleagues.[196]

Concerning the inefficiency of the organizational mindset, an organization which remains on the global optimum of the NK landscape equivalent to a relative learning success of 1.0, does not show a puzzling persistence thus making the diagnosis of an organizational path obsolete. On the global optimum, there is no incentive for the organization to change its state of mind. Consequently, the low number of different mindsets in the organization has to be accompanied by an organizational learning success which is below 1.0 indicating that a better alternative is still available.

Following on from this, we conclude that the performance achieved by the organization specifies the significance of the lock-in state: The lower the organizational performance, the higher the discrepancy between the organizational belief-set and the optimal configuration of beliefs.

The path-dependent outcome is the result of a simulated process unfolding in simulated time. The concept of time in simulation models is seldom dealt with. It hides in the control variable ticks which defines the time steps in the simulation. In the subsequent chapter, we clarify the concept of time in our model.

5.6 Time in the Model

A simulated system can be conceived as *"a collection of entities that interact together over time to accomplish a set of goals or objectives"* (Kheir, 1988:98). One of the greatest benefits of most simulations is that they offer the possibility to follow the development of a system through (simulated) time. As we have seen in the above described pseudo code,[197] time in our model proceeds in discrete and equidistant time steps or, as they are called in many simulations, ticks. These time steps are occurrences in time that alter the state of the system. At each time step the same

[196] As described in chapter 4.3, exchanging knowledge with others which in our model is moderated by the code is a mechanism of exploration for the individuals.

[197] See Figure 18.

functions are applied and all the state variables of the system, as for example the learning success of the organization and its members, are updated. This contrasts with approaches of discrete event simulation, in which only specific events result in an updating of some of the state variables of the system (Gilbert & Troitzsch, 2005:79). Time in our model, however, must be considered as a continuous flow which is simulated by repeating the same behavioral rules for the agents for every time step.[198]

Having clarified how time proceeds in our model, another significant aspect is open for discussion: the relationship between simulated time and real time. This relationship is a difficult one. In our model, it is partly defined by the initial conditions which are simulated. The simulated organization starts with a random distribution of beliefs inside the organization; each member has a belief-set which initially is assigned randomly. This state in which the organization on average has no knowledge (March, 1991:75) most closely corresponds to the conditions at the founding of the organization which is a common and often implicit assumption in almost all organizational learning models (March, 1991; Rodan, 2005; Miller, Zhao, & Calantone, 2006; Fang, Lee, & Schilling, 2010).

We therefore know at which point in time we start but relating the length of simulated time or, in other words, the number of ticks to real time is difficult. Concerning the length of the process, we have to stick to relative evaluations. This means that the time until the convergence of beliefs can only be assessed in relation to alternative parameter settings, much in the way it was originally processed by March (1991). Thus an organization will converge faster or slower, show a better or worse performance due to its learning conditions and the environment it encounters. To relate it more closely to reality would require a much more complex model which in turn would significantly affect its robustness.[199] Integrating more and detailed variables into the model – e.g. refining the probability parameters of the learning rates - would increase the difficulties in assessing the model behavior exponentially (Lazer & Friedman, 2007:672). It is the interaction between variables which complicates understanding simulation models (Lorscheid, Heine & Meyer, 2011:7). Here we again encounter the tension between keeping models simple and making them more

[198] In chapter 6.1.4 in the model configuration, we determine the number of ticks necessary for our experiments.

[199] See chapter 6.5 on the robustness of the model.

elaborate.[200] As the focus of our model is on understanding how the dynamics in the model unfold under different environmental conditions, we consider a relative approach sufficient.

5.7 Computational Implementation of the Integrated Model

In the computational implementation, the model as described in the preceding chapters is transferred into program code. In the following section, we first describe which programming language and simulation environment we chose for implementing the model. Another important step in the implementation of the model pertains to its verification with which we deal subsequently.

5.7.1 Programming Language and Simulation Environment

Implementing the model involves deciding on a programming language and an environment in which to run the simulation. Here, the choice is either to work with one of the pre-designed toolkits and packages which help with the construction of a simulation or to design one's own simulation program. Packages offer a wide functionality and limit programming effort but they are not applicable for every modeling task (Gilbert & Troitzsch, 2005:21). Packages such as NetLogo or Anylogic, feature predesigned components, for example network structures and behavioral rules for the agents and can be employed with great flexibility.[201] However, in our case as we employ an NK landscape to represent the organizational environment, the usage of simulation packages and toolkits which simplify the programming task is impossible. Setting up the NK landscape requires unrestricted programming which is then difficult to implement in a pre-designed framework. If the model builder does not rely on the

[200] See also chapter 3.2.2 on the benefits and limitations of simple models.

[201] NetLogo is Java based internally but the language that the programmer uses is Logo, a procedure-oriented language. Despite being easy to learn, it offers far less adaptability of the program code when changes or extensions are required. The agents in NetLogo are usually situated on a grid. Anylogic is a commercial toolkit which is often used for simulating business and transport processes. It is also offers a simplified Java programming environment and its benefits lie mainly in providing already-existing program components such as different network types.
For more information on NetLogo, see http://ccl.northwestern.edu/netlogo/.
For more information on Anylogic, see http://www.xjtek.com/.

aid of a package, several criteria for the choice of a programming language have to be taken into consideration (Gilbert & Troitzsch, 2005:21-22).

The first relates to the structure of the language. It should allow incremental refinement by enabling easy cycling between coding, testing and modifying. This gives the researcher the possibility to alter the program code quickly in case bugs are detected or changes to the program structure and methods become necessary. In most cases, this will point the researcher to object-oriented programming languages such as Java or C++.

Secondly and very importantly for the verification phase, the language should allow easy and rapid debugging. This is often determined by the programming editor and is also a matter of the available graphics libraries which make the large amounts of data, usually generated by simulations, visually accessible for the researcher. Good editors provide debugging help and the graphical output of simulation data furthermore points the researcher to logical mistakes in the program code which do not appear in an editor debugging facility. Debugging the simulation program requires substantial amounts of time; therefore this requirement is of special importance.

The third requirement relates to the efficiency of the simulation. Simulations almost always require many hundreds or even thousands of repetitions (or, in other words, runs), for different parameter combinations; in consequence the simulation should run as efficiently as possible.

Last but not least, most research communities have their own preferences when it comes to programming languages. Sticking to the languages used in similar models makes the program code accessible for other researchers and hence furthers continuing work. It also enables researchers to exchange models and find model lay-outs to build their programming on.

We decided on a Java based approach in an Eclipse programming environment.[202] This choice was guided by the preferences of the research community working with organizational learning models but also due to many of the factors described above. In

[202] We worked with the Java Development Kit (JDK) 1.6 in the Eclipse Software Development Kit (SDK) 3.6.1.
For the JDK, see http://www.oracle.com/technetwork/java/javase/downloads/index.html.
For the Eclipse SDK see http://www.eclipse.org/platform.

addition to being able to build on already established models and compare the coding, Java qualifies as a fairly simple object-oriented programming language (Krüger & Stark, 2009) which allows the program to be given a sensible class and method structure, thereby making it easily extendable.

With regard to debugging facilities, the Eclipse programming environment helped in detecting syntax errors. The massive amounts of data the simulation produced were made accessible by using the JFreeChart graphic library.[203] The resulting possibility of following the history of simulation runs graphically also allowed correcting logical mistakes in the program code. As for the efficiency requirement, Java is not a compiled language which means that Java programs are not directly executed by the processor. Instead, their byte code has to be translated by an interpreter ((Krüger & Stark, 2009:51). For this reason, Java programs are often still considered to be rather slow. However, nowadays the difference between compilation and interpretation is much less than it used to be (Gilbert & Troitzsch, 2005:21; Krüger & Stark, 2009:51) so that this criterion can be given less weight.

The programming orientation of the relevant research community must be considered very important as it ensures that the model is well understood and adds most easily to the already acquired knowledge of other researchers. We checked several modeling approaches in the research community to see if they were suitable for incorporating the aspects of our model. Unfortunately, it is still not common to make the programming code of published models easily accessible for fellow researchers. We mainly compared the coding of two approaches. The Sendero project provides a basic framework for building an NK landscape model using Java language (Vidgen & Padget, 2009).[204] The project aims to provide a general framework for organizational research involving the NK approach, and therefore using it for our purposes would make the code unnecessarily complicated. Lazer & Friedman (2007) provide one of the few openly available model codes and share this code according to the creative

[203] The JFreeChart library provides facilities to program various types of charts. In the simulation JFreeChart was used to follow the dependent variables in the history of the simulation. We used the version JFreeChart 1.0.13. For the JFreeChart library, see http://www.jfree.org/jfreechart/.

[204] For the sendero project, see http://wiki.bath.ac.uk/display/sendero/NKC;jsessionid=155F59835B8395B55D5F045E19B89990. The simulation here is implemented in a REPAST modeling environment.

commons attribution-share-alike license.[205] Although the model of Lazer & Friedman (2007) focuses on knowledge exchange processes in a network setting, we found their well-documented and structured coding approach most helpful for our purposes. We altered their model with respect to the organizational structure, implementing here the structure featured in March's (1991) model, the order, working, and interaction of the learning processes, the implementation of turbulence in the NK landscape, and the graphical as well as the numerical output.

5.7.2 Model Verification

After the model has been formalized and embedded into program code, its functioning has to be verified and validated. Whereas the model validation assesses whether the model is a good approximation of the modeled phenomenon,[206] in the model verification, the modeler first checks that the simulation program works as it is supposed to do. This debugging procedure ensures that the model output is not simply due to programming mistakes or systematic errors[207] but is the result of the model's designed functioning (Gilbert & Troitzsch, 2005:22; Davis, Eisenhardt, & Bingham, 2007:493).

Simulations often involve complex program code which has to be debugged carefully in a sequential way by considering the output of every method in the code. Verification is further complicated as in most models random number generators yield at least slightly different results for every run of the model. It is therefore often only a distribution of output values which can be assessed by the modeler. Gilbert & Troitzsch (2005:22) recommend meeting these difficulties by establishing test cases or extreme cases for which the model behavior can be easily predicted. With regard to our model, we isolated the learning processes and checked model behavior in differently complex environments. The model results were visualized as graphics using the JFreeChart library which simplified the identification of mistakes. The test procedure was accompanied by a method-by-method debugging approach. This

[205] For creative commons, see http://creativecommons.org/licenses/by-nc-sa/3.0/us/.

[206] See chapter 6.2 where the model is anchored in existing research.

[207] Systematic behavior in the model is also called an artifact (Wijermans, 2011:71). A typical mistake in an agent-based model producing systematic behavior involves the sequence in which agents act.

additionally provided a fine-grained insight into the working of the simulation as for the concerned methods debugging tools were written to check their internal functioning. For example, debugging tools were used to follow the behavior of individual agents, their links to other agents, changes in their bit string and how they incorporate new elements into their bit string. As the program code is an alteration and extension of the code of Lazer & Friedman (2007), we put a special emphasis on the changed and added elements, especially the code structure, the learning processes, the implementation of turbulence in the NK landscape, and the output facilities. Parts of the model were also written together with and checked by an experienced Java programmer.

In chapter 5, we described our integrated model of path-dependent learning. We gave an outline of the model structure[208] and delineated its elements and processes. The learning processes in the model are comprised of behavioral rules for the agents. We described their sequencing in terms of a pseudo code.[209] In the classification of variables, we specified the model's independent and dependent variables and, to make the model more transparent, outlined its control variables. Following on from our definition of variables, we specified path dependence in their terms. To conclude the model description, we discussed the concept of time in our model. In the last part of chapter 5, we referred to the way the model was implemented into program code and the verification of the program.

The subsequent chapter is concerned with the experiments conducted with the described model and aims to answer the research question.

[208] See Figure 16.

[209] See Figure 18.

6 SIMULATION EXPERIMENTS

In the preceding chapter, we described our agent-based model which integrates the dynamics of mutual and individual learning. Having formalized our model's processes and variables, we continue in this chapter with the simulation experiments. As a first step, we are concerned with preparing the model for the experimentation phase. Here, we give an outline of the parameter ranges inquired into in the simulation and specify the control variables. On this basis, we continue by anchoring the model in existing research, thereby proving its ability to replicate results from established and renowned models. This step can therefore be considered the validation of the model. Subsequently, we proceed to the core of the experimental chapter: the simulation experiments which aim at answering the research question. Here, we conduct two sets of experiments: The first one focuses on the impact of environmental complexity on path-dependent organizational learning, while the second one takes into consideration the impact of environmental turbulence as specified according to the frequency and scope of change.

6.1 Experimental Framework

In this chapter, we configure the model and prepare it for the experimental phase.[210] This comprises specifying the parameter ranges of the independent variables,[211] determining the number of environmental dimensions (N) and the corresponding number of agents (pop), selecting an appropriate experimental design and estimating the error variance in the model to determine its number of iterations ($runs$) in each setting.

As we consider validating the model a very important part of simulation studies, validation will be dealt with in a separate chapter specifically dedicated to this aspect.

[210] See the simulation life cycle as outlined in Figure 7. In the present chapter, we are concerned with specifying the experimental model.

[211] Lorscheid, Heine, & Meyer (2011) differ between dependent and independent variables in the model and the response variables and factors in the experimental design. Response variables are the output variables of the model and factors specify the experimental settings. Although this differentiation in some cases is necessary we do not use it here, as in our model the difference between dependent variables and response variables as well as independent variables and factors is negligible.

In our case, the validation involves conducting experiments with the model which replicate behavior shown by models of mutual learning or models dealing with search processes in NK frameworks. In this way, the model is anchored in existing research.

In the following chapter, we outline the ranges of the simulation parameters into which we inquired.

6.1.1 Parameter Ranges

The specification of the parameter ranges for the independent and control variables is based on our classification of variables and exhibits the minimum and maximum values for the listed parameters with which we worked in the simulation. Figure 20 provides an overview in which for each of our variables the relevant parameter ranges are outlined.

Independent variables	Parameter name	Parameter range
Complexity of environment	K	[0; N-1]
Frequency of env. change	x	[5; ticks]
Scope of env. Change	τ	[0.0; 0.8]
Speed of learning by the code	probabilityCode	[0.0; 0.9]
Speed of learning from code	probabilityAgents	[0.0; 0.9]
Speed of individual learning	probabilityExplore	[0.0; 0.9]

Control variables	Parameter name	Parameter range
Number of ticks	ticks	see required # of ticks
Number of runs	runs	see required # of runs
Number of agents	pop	[25+1; 100+1]
Size of superior group, elite size (number of agents code accesses for learning)	numBetterPerf	[1; 20]
Number of env. dimensions	N	[10; 20]
Keep or abolish dependencies of env. dimensions on change	keepDependenciesOnChange	true; false

Figure 20: Parameter ranges of independent and control variables[212]

[212] Concerning the parameter ranges of pop: the values $x + 1$ capture the number of organizational members plus the code.

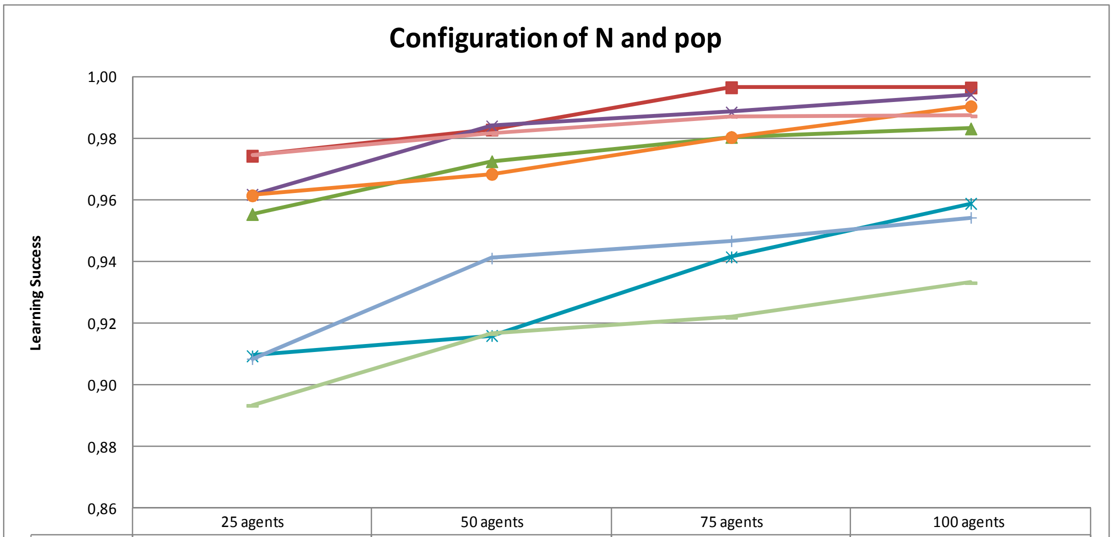
For the control variables the parameter ranges indicate how we inquired into their influence on the simulation outcome and will mostly be dealt with in the following chapters concerning the preparation of the simulation experiments. The target here is to get a clearer picture of their impact on the simulation outcome so that the control variables can be specified plausibly (Lorscheid, Meyer, & Heine, 2010:13).

For the independent variables, which in contrast to the control variables are of interest for the research focus, the parameter ranges mainly refer to the settings in the simulation experiments. The parameter ranges specifying the speed of the learning processes where set to be consistent with March (1991). A learning speed of 0.0 in our model indicates that the process is inactive, a setting used for testing the extreme cases of solely mutual or individual learning. The ranges of the environmental parameters τ and x do not cover the complete range available. We also conducted test runs covering the complete parameter range but found that a broader range provided no additional value or did not contribute to a clearer demonstration of the simulation results. For example, in case of $\tau = 0.0$, past performance values in the NK landscape are completely uncorrelated to future performance values (see also Siggelkow & Rivkin, 2005:104) and organizational performance becomes merely a product of chance.

In the following chapters, we describe how the control variables were determined, starting with the configuration of the interdependent parameters N and pop.

6.1.2 Configuration of N and pop

As the difficulty of the search problem also depends on the number of agents searching the problem landscape, the number of environmental dimensions (N) has to be aligned with the number of agents (pop). Both, N and pop, are considered control variables and were determined in a separate test ahead of the experiments for which they are considered constant configurations of the organization and its environment. We conducted tests with landscapes differing in their number of dimensions and their complexity for four different organization sizes.[213] The results of the tests are summarized in the following figure.



	25 agents	50 agents	75 agents	100 agents
N10 K3	0,97	0,98	1,00	1,00
N10 K8	0,96	0,97	0,98	0,98
N15 K3	0,96	0,98	0,99	0,99
N15 K10	0,91	0,92	0,94	0,96
N18 K3	0,96	0,97	0,98	0,99
N18 K10	0,91	0,94	0,95	0,95
N20 K3	0,97	0,98	0,99	0,99
N20 K10	0,89	0,92	0,92	0,93

Figure 21: Organizational learning success for the different settings of N and pop (p_{expl}=1.0; p_a=0.1; p_c=0.9)[214]

As expected, we experience an increase in organizational performance with a rising number of learners in the system. Systems involving many agents (here 100) would need to run an exponentially larger problem landscape. As the number of locations in the problem landscape is determined by 2^N, landscapes with a high N are much more time consuming to generate. It is therefore recommendable to select a landscape configuration which makes the learning task difficult enough to provide meaningful results for all landscape complexities but also to bear in mind the simulation

[213] The tests are conducted for beneficial learning conditions where a high organizational performance can be expected as the setting of N and pop has to be chosen on the basis that it provides sufficient difficulty of the learning task.

[214] The number specified in the figure refers to the number of organizational members. For the total number of agents (including the code) the numbers have to be increased by one.

duration.[215] We therefore decided to proceed with the following configuration: The environment will encompass 15 dimensions, and the organization will consist of 50 members plus the code. With this environmental configuration the search space encompasses 32768 different solutions and depending on K a varying number of local optima.

Generating the NK landscape is the most time-consuming task in NK simulations (Ganco & Hoetker, 2008:7). We therefore decided to create the NK landscapes ahead of the simulation runs. For the experiments executed with the model, we generated 1000 NK spaces with $N = 15$ and varying complexity. NK spaces of defined N and K still vary significantly in their number of local optima (Rivkin & Siggelkow, 2007). Consequently, it is necessary to account for this variation by running each model iteration in an experiment on a different NK space. Still, experiments which involve similar environmental configurations with respect to K access the same NK spaces. We go into more detail on this in the next chapter dealing with the specification of the required number of model runs.

6.1.3 Required number of model runs

The varying number of local optima in an NK space is one of the nuisance factors in our model. Another, for example, is the randomly determined position of the agents in the NK landscape at the beginning of the simulation. These and similar factors are sources of variation in a simulation model even when the parameters themselves are not varied. Thus, a model for each configuration of parameters has to be run repeatedly to achieve statistically meaningful results. The required number of model iterations can be determined by estimating the experimental error variance. The experimental error is the variation in the simulation output between different runs of similar settings. As recommended by Lorscheid, Heine, Meyer (2011:12-17) we measured this variability in the data by using the coefficient of variance.

[215] In chapter 5.6, we already pointed out that the simulation produces relative results that have to be assessed in comparison with results obtained under different conditions.

The coefficient of variance is defined as the ratio of the standard deviation of a number of measurements of the output variables to the arithmetic mean:

$$c_v = \frac{s}{\mu}$$

We defined a broad number of parameter settings, or in other words design points for which we ran our model for different numbers of runs.[216] For each specific design point, the coefficients of variance for the various amounts of runs are compared. If increasing the number of runs does not alter the coefficient of variance, the necessary amount of runs has been determined. We found that for most design points the coefficient of variance stayed stable for less than 500 runs, for one design point 600 runs were necessary. All results reported for the experiments will, therefore, be based on 600 iterations of the model.[217]

6.1.4 Required number of ticks

The number of time steps in a model ($ticks$) is also considered a control variable which has to be set before conducting the experiments. The number of time steps in our experiments depends on the tendency of the model to converge or to go through ongoing learning processes. If the experimental settings lead to a convergence of the model, the number of time steps should be sufficient to show convergence and capture possible variations of the convergence time in different runs. If the model cycles through ongoing learning processes, we must at least be able to capture enough cycles to show the behavioral pattern of the organization (Siggelkow & Rivkin, 2005:119).[218]

Of course, the duration of a simulation must be long enough to enable the researcher to assess the behavior of his model. In a model which explores the nature of path

[216] For the specification of the design points, see Appendix D, Table 20. The design points capture different parameter combinations of the environmental complexity and learning conditions in order to cover the complete range of behavior of the model.

[217] For the results of the estimation of error variance, see Appendix D, Table 21. The results have been achieved for the same setting of the control variables which was used for the first and second set of experiments. Not specifying the size of the group the code accesses for learning ($numBetterPerf$), as is the case for the original March (1991) logic, in complex environment leads to a fluctuating behavior of the output variables.

[218] For an assessment of the required number of ticks for the design points in a stable model, see Appendix E.

dependence, one might consider the time to reach the lock-in state a valid indicator. Still, when configuring a simulation, its duration, measured as its number of ticks, is an explorative task. Even if we consider our model to lead to a convergence of beliefs, at least for some parameter settings, we first have to explore which number of ticks is required to reach convergence also taking into consideration possible variations in the time to convergence from run to run. Nevertheless, for a stable environment, the duration of the simulation must at least encompass the time necessary for the system to converge on a unified system of beliefs.

A turbulent environment requires a different approach. In these environments, the relation between the time to convergence and the frequency of change in the environment becomes important.[219] To reliably determine the learning pattern of the organization, we have to follow the organization for a number of environmental cycles. This enables us to find out if the patterns themselves are similar across cycles and to compare organizational performance with different parameter settings (Siggelkow & Rivkin, 2005:119).

6.1.5 Experimental Design

The experiments conducted with the model reflect first of all the research question how the environmental conditions influence organizational path dependence. Furthermore, we tried to point out and investigate some of the interesting avenues that appeared during the research.

The approach followed here can be best described as one of a stepwise increase in model scope and complexity.[220] In each step, we introduce more of the described parameters. By dealing with the model in this fashion, we ensure that we understand the effects of simple processes before we make them more complicated and create interactions with other parameters. The results achieved for a simpler setting can thus provide a basis from which to explore a more comprehensive scenario by guiding the preceding parameter settings.

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[219] See chapter 6.4 for a detailed explanation of the relation between learning and environmental turbulence.

[220] See on this also Axelrod's (1997) KISS principle and chapter 3.2.2.

We start by exploring the model behavior in a context which was already described by March (1991), mutual learning in a simple environment and in this way anchor the model in existing research. Then we conduct the first set of experiments which deal with the impact of problem complexity on organizational learning. Here again, we start out with a reduced scope showing the effects of problem complexity for fast and slow learning in organizations. In a second step, we activate the competence-enhancing learning process of the individuals introducing a constant stream of variation into the organization. The results of the experiments can therefore be linked directly to the different dynamics working in the model. The second set of experiments adds turbulence to an already complex environment and focuses on the effects of varying its frequency and its scope. Similar to the first set of experiments, we start out with exploring the behavior of the organization under conditions of fast and slow learning before we introduce individual learning.

Having specified our experimental framework in the subsequent chapters, we proceed to the validation of our model.

6.2 Model Validation: Anchoring the Model in Existing Research

While verification refers to the functioning of the program code, *"validation concerns whether the simulation is a good model of the target."* (Gilbert & Troitzsch, 2005:23).[221]

Gilbert & Troitzsch (2005:23-24) note that if a model is intentionally abstract, validation can be hard since establishing a connection between the model outcomes and empirical data may prove difficult. Harrison et al. (2007:1242) argue in a similar vein when they consider empirical grounding mostly relevant for simulations which aim at prediction and model closely to the target instead of modeling in a simplified and abstract way.[222] Therefore theoretical models which are highly simplified have to embark on validation in a different way. A legitimate approach concerns anchoring the

[221] Whereas verification deals with the internal validity of the research, validation focuses on the external validity (Gilbert & Troitzsch, 2005:23).

[222] Harrison et al. (2007:1242) claim that *"[s]imulations can be used to explore the consequences of theoretically derived processes, for example, even if the outcomes cannot be readily assessed empirically."*

model in existing (simulation) research. By fulfilling at least a minimum requirement for validation, here the model can be shown to reproduce results of other theoretical models which are acknowledged in the respective research community.[223]

In the validation process, we therefore show to what extent our model can reproduce results that have been achieved already by established models. In this way, the results in this chapter are used to indicate if our simulation can be considered a good model of the target phenomenon (Wijermans, 2011:71). Similar to the structure chosen for the experiments which explore the effects of environmental complexity and turbulence, we inquire into the dynamics of mutual learning and competence-enhancing learning at the individual level separately. As a first step, we try to replicate the results achieved in March's model of mutual learning (1991). In a second step, we validate competence-enhancing learning in an NK framework connecting our model to models of local search as described in chapter 4.2.3.

Usually, the results of the simulation throughout the experiments will be reported as history charts of the four dependent variables (see Figure 22):

- the average learning success of the organizational members ($learning\ success,$ in red),
- the learning success of the organization ($code\ score$, in yellow),
- the number of different beliefs in the organization ($unique\ solutions$, in green), and
- the belief heterogeneity describing how much the beliefs of the organizational members differ ($heterogeneity$, in blue).

[223] Burton & Obel (1995:65) consider content validity an important criterion for the overall validity of simulations. Content validity answers the question if the model makes sense to a group of experts for the modeled phenomenon.

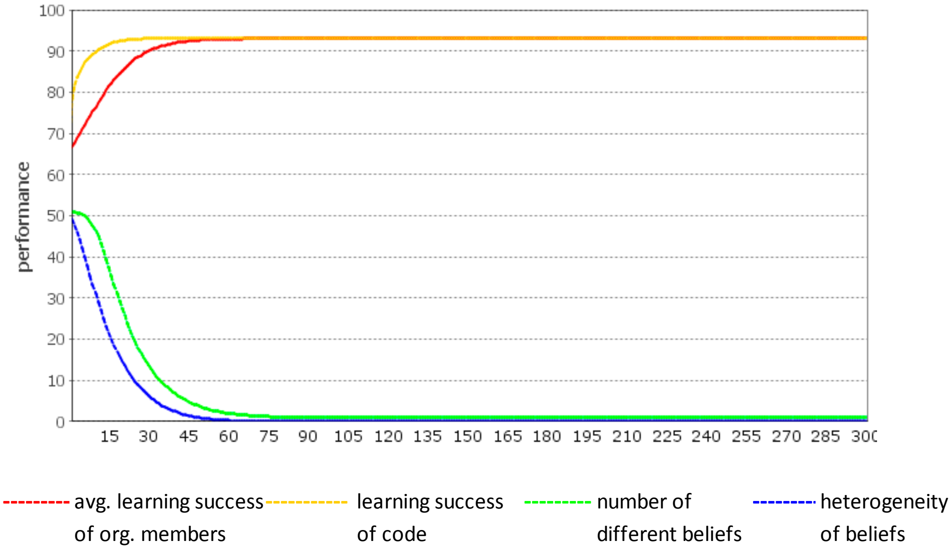


Figure 22: Example for history chart of organizational learning

The x-axis shows the time steps covered in the simulation, the y-axis displays output values. A score of 1.0 or 100% for the learning success indicates that the organization has reached the global optimum in the NK landscape (in stable settings). In the beginning, the number of unique solutions or beliefs in the organization is 50 plus the code solution as all agents in the simulation initially are randomly distributed in the problem landscape. Due to mutual learning of code and individuals the organization converges on a homogenous belief-set which in the example does not represent the best solution attainable. As outlined in chapter 6.1.3 all results in this chapter (if not indicated otherwise) are average values of the dependent variables over 600 model runs.

6.2.1 March (1991): Mutual Learning in Simple Environments

Fast learning is not necessarily beneficial for organizations. This was the most astonishing result of March's (1991) model of mutual learning. If the organizational level learns from the individual level and vice versa, beliefs in the organization converge. Although this convergence generally contributes to knowledge for both the organization and the individual, as neither the organization nor the individual in this model are able to learn in isolation (Rodan, 2005:408), the process might be harmed by its speed. There is a danger that the individuals in the organization adjust to the code before the code can learn from their diversity (March, 1991:85). Potentially useful solutions get eliminated prematurely. The organizational performance is summarized for different combinations of learning speeds. Parameter p_1 in March (1991) is reflected by p_a in our model, the speed of learning from the code or in other words socialization. Parameter p_2 reflects p_c in our model, it is the speed of learning by the code or how fast the code incorporates knowledge from the organizational members.

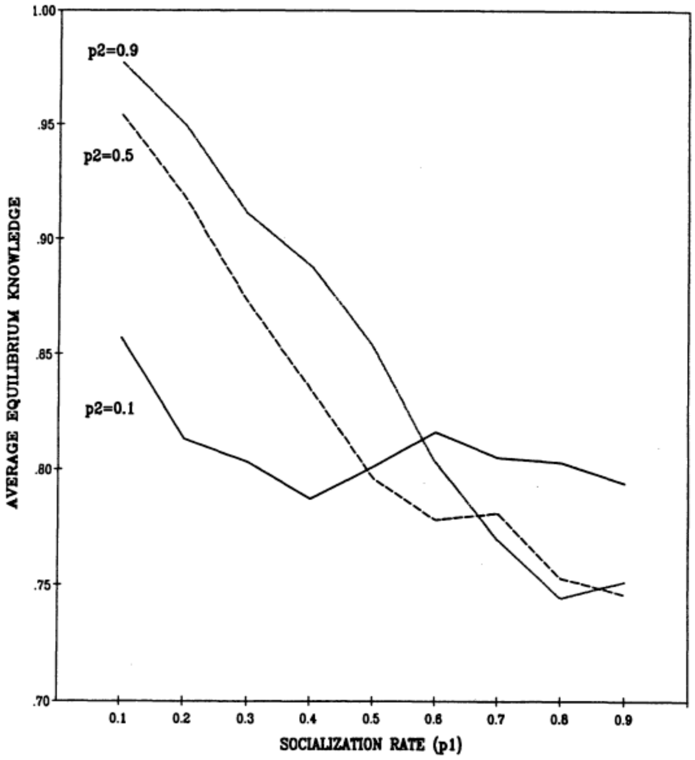


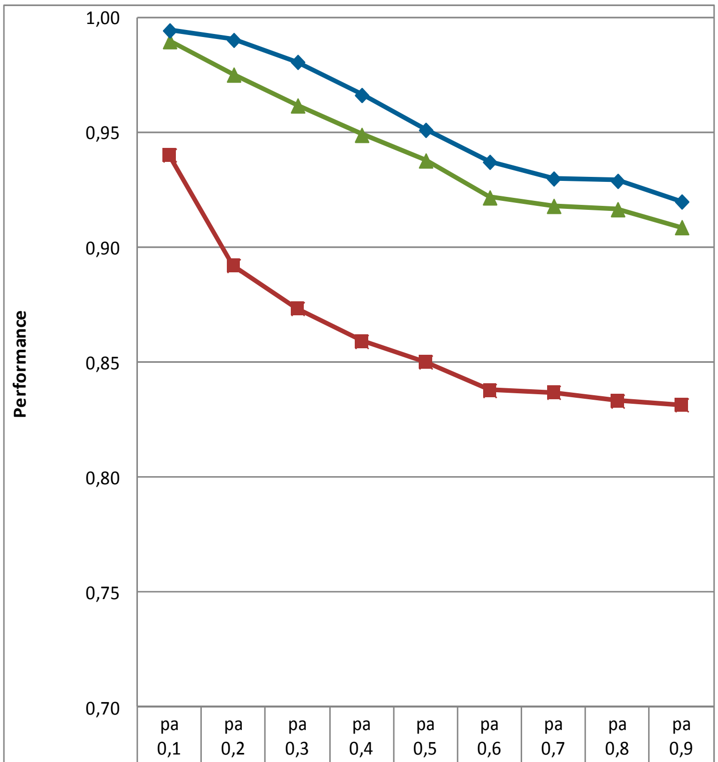
FIGURE 1. Effect of Learning Rates (p_1, p_2) on Equilibrium Knowledge. $M = 30$; $N = 50$; 80 Iterations.

Figure 23: Comparison of learning regimes in March (1991:80)

From Figure 23, we deduce that for different regimes of learning by the code, fast socialization of the organizational members to the code always proves detrimental to organizational performance. Slower socialization leads to greater organizational knowledge. The organization performs best when the individuals learn slowly from the code but the code in turn learns rapidly from the individuals.

Our model is not entirely comparable to March (1991) as it builds on an NK landscape approach to simulate the individual learning process. To validate it, we can nevertheless chose a configuration which brings it as close to the original mutual learning model as possible. We therefore switch off the individual learning process ($p_{expl} = 0.0$) and focus on merely mutual learning from and by the code. Learning by the code is conducted similarly to the process in the original model; the code selects all members who perform better than the code to learn from their beliefs and also weights the frequency with which a belief is set to 0 or 1 within this group of superior performers. March (1991) tested organizational learning in an environment which is not complex. We therefore have to set K in our model to 0 to achieve a simple environment with merely one optimum. Both models define an organization size of 50 members but they differ in the number of environmental dimensions. The individuals in March's model have to deal with an environment consisting of 30 dimensions, a landscape size which, because of computational power and simulation duration, was not feasible for us.[224] In our model N is set to 15. While the results of the original model are based on 80 iterations of the model, our model was run 600 times for each combination of p_a and p_c. We tested the specified mutual learning model in the simple environment for the same combinations of learning parameters as in March (1991) with the following result:

[224] Another difference concerns the belief-set of the organizational members. Different to an NK framework, in March (1991) the belief-sets of the members can take on the values of $-1, 0$ and 1. The organizational members start their learning with belief-sets in which $-1, 0$, and 1 are distributed with equal probability (March, 1991:74-75).



	pa 0,1	pa 0,2	pa 0,3	pa 0,4	pa 0,5	pa 0,6	pa 0,7	pa 0,8	pa 0,9
Pc=0,1	0,940	0,892	0,873	0,859	0,850	0,838	0,837	0,833	0,832
Pc=0,5	0,990	0,975	0,962	0,949	0,938	0,922	0,918	0,917	0,909
Pc=0,9	0,994	0,990	0,981	0,966	0,951	0,937	0,930	0,929	0,920

Figure 24: Effect of learning rates on system performance in a simple environment with solely mutual learning (K=0; p_{expl}=0.0)

Similar to March (1991), we also experience the basic dynamic of a mutual learning model, fast learning from the code proves detrimental for organizational learning performance. Slower socialization turns out to be beneficial over all learning regimes of the code ($p_c = 0.1;\ 0.5;\ 0.9$). The difference between the high and medium learning regimes of the code ($p_c = 0.5;\ 0.9$) as in March (1991) is not very pronounced. Despite these similarities in the qualitative results, as could be anticipated, the quantitative results vary. The organization in our model in general performs better. With a simple environment ($K = 0$) consisting of merely 15 dimensions for a comparable number of agents this was the expected result.

What we could not replicate in our model was that in case of rapid socialization, the organization performs better if the code learns more slowly. This result was not explained in any more detail by March (1991) but seems to be due to the fact that in his model the code belief-set at the beginning of the simulation is set to 0 for each dimension. In learning from the code, individuals are not affected by dimensions in the code of 0 value (as this should express no belief of the code on the specific dimension). Naturally, slow learning by the code is then able to prolong the complete learning process as the code in this case stays longer in the state of not knowing and, consequently exerts no influence on the agents. In this way, the socialization process is artificially prolonged with the beneficial consequences we can expect for organizational performance.

Our model therefore confirms what March (1991) noted:

> *"The gains to individuals from adapting rapidly to the code (which is consistently closer to reality than the average individual) are offset by second-order losses stemming from the fact that the code can learn only from individuals who deviate from it."* (March, 1991:76).

Indeed, the individuals in adapting rapidly to the code improve their average knowledge state (see also Figure 23) as the code tends to know more than the average organizational members. In our model, this is also reflected by an increase of the average knowledge in the organization. Given this basic dynamic, we should expect a further reduction in code knowledge if it is unlikely that the code incorporates knowledge from the better performers as it is the case for slow learning by the code. A regime of fast learning by the code in this case would ensure that, while the organizational members converge on the code belief-set, at least deviating ideas which perform better than the code are able to influence its knowledge state. Consequently, we argue in accordance with March (1991) that by far the best learning conditions for an organization in mutual learning are given when the organizational level is able to acquire new knowledge quickly while the organizational members are only slowly socialized to the organizational belief-set. The worst learning conditions are characterized by fast learning on the individual level which in our model is accompanied with a code which only reluctantly alters its knowledge state, in other words which learns slowly.

These beneficial and detrimental learning conditions for the following experiments will be the preferred settings to test organizational leaning in the differing scenarios in the experiments.

6.2.2 Search in an NK Landscape: Competence-Enhancing Learning

In mutual learning models, individuals are unable to learn in isolation. Only in exchange with others (often via an organizational code) are the individuals able to improve their knowledge. But, generally, individuals do not only learn by exchange of knowledge with other individuals, they also improve their knowledge based on their personal experience. This incremental learning is subject to many constraints which give it a highly path-dependent character. Individuals walk their learning trajectory based on their past knowledge and their limited oversight. Each individual in a system bare of any exchange of knowledge would thus be required to stay on his personal learning path (Ackermann, 2003:243).

We test this proposition in our integrated model by ruling out any exchange processes via the organizational code. Learning by and from the code is therefore set to 0. Individual learning was modeled as a process of local search in the NK landscape. We test this local search process in differently complex landscapes.

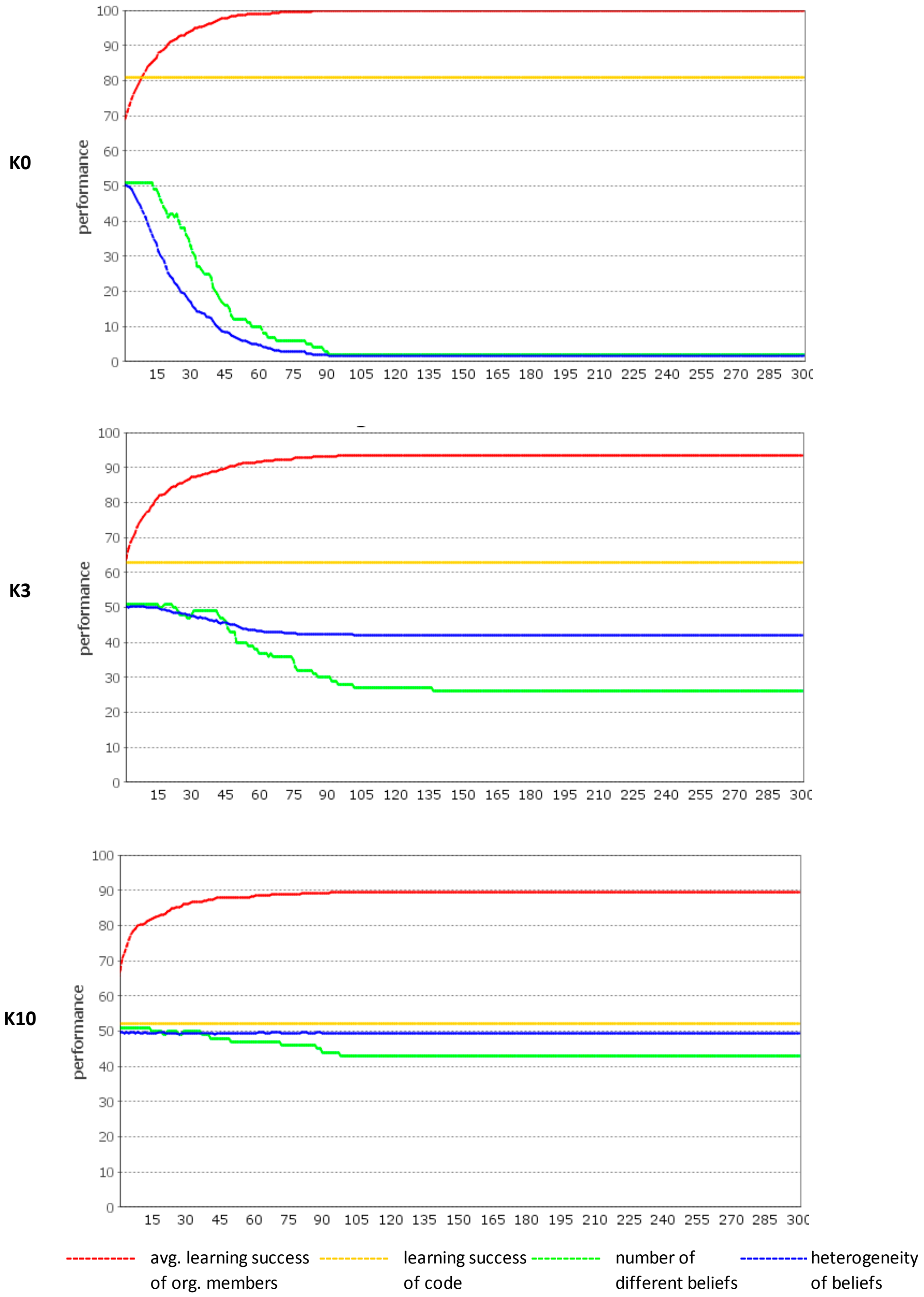


Figure 25: Solely individual learning in simple and complex environments (p_{expl}=0.9; p_a=0.0; p_c=0.0)

Figure 25 shows the organizational performance with solely individual learning in a simple ($K = 0$) and medium ($K = 3$) to highly complex environments ($K = 10$). In a simple setting, all organizational members are able to learn the best representation of the organizational environment. The average learning success in the organization is 1.0 which shows that all individuals arrive at the global optimum. The number of different solutions present in the organization declines to 1. This convergence is not due to a scenario of knowledge exchange but a consequence of the process of individual learning which, independent from one another, leads all organizational members to the global peak in the NK landscape.[225]

In this scenario the code forfeits all learning abilities and thus the organizational score does not improve. The result implies that, if the problem is adequately simple, even very limited learning abilities are sufficient to solve it.[226] In case of complex environments, we experience that the individual learning process leads the organizational members to the local optima in the landscape. The average score in the organization improves as the individuals acquire better representations of the environment but the number of different solutions does not drop to 1. Instead we see that in a medium complex environment it falls to a certain level and remains constant. We conclude that some of the individuals in the organization have acquired similar representations. The local search process has led the individuals equipped with different knowledge endowments or different starting positions in NK to the same local optima from which they then fail to remove themselves. In a rugged space, local search implies that agents move uphill incrementally without having the possibility to move downhill or jump in the landscape (Lazer & Friedman, 2007:674; Ganco & Hoetker, 2008:10). Because we eliminated the social context from our model by ruling out communication and interaction, the individuals in the organization possess divergent mental models (Ackermann, 2003:244). A comparison with the highly complex environment shows us that the more complex the learning setting, the higher the divergence in mental models. This is due to the fact that a more complex environment involves more local optima which prove to be competence traps for the learning individuals (Levinthal, 1997; Rivkin, 2001). In a more complex environment, lock-ins due to myopic search become more common.

[225] The result is similar to the one achieved for local search of the department managers in a decentralized organization (Siggelkow & Rivkin, 2005:110).

[226] Research on organizational design found out that in simple environments almost all designs are able to perform well (Fang, Lee, & Schilling, 2010:634).

In a scenario of solely individual learning, the individuals in the simulation behave as expected. The intelligence of organizations strongly relies on the interaction of both learning processes: mutual learning and individual learning.

6.3 First Set of Experiments: Path-Dependent Organizational Learning in a Complex Environment

The structure of our experiments reflects a step-wise increase in model scope and intricacy (Davis, Eisenhardt, & Bingham, 2007:482).[227] We start by inquiring into the effects of environmental complexity on organizational learning. Understanding the model's behavior in differently complex settings provides a suitable basis for exploring the additional effects of environmental turbulence.

In our first set of experiments, the environment is therefore not subject to any changes but stays constant for the duration of the simulation. Again, the experiments conducted on the effects of complex environments follow the approach of increasing the intricacy of the model when we inquire into the consequences of solely mutual learning and based on this add individual learning. First, we relate March's (1991) model of mutual learning to regimes of varying complexity. Second, we test organizational behavior in complex settings when the mutual learning process is complemented by individual learning.

6.3.1 Recapitulation: Problem Outline

In path dependence theory the role of environmental complexity for the unfolding of path dependence is unclear. While some approaches argue along the lines of complexity being a necessary condition for path dependence to unfold (North, 1990:95) or to increase the likelihood of path dependence (Pierson, 2000:259-261), other lines of argument distance themselves from the thought that complexity necessarily leads to path dependence (Sydow, Schreyögg, & Koch, 2009:701). In the

[227] See chapter 6.1.5.

following experiments we inquire into the role of complexity for self-reinforcing learning effects in organizations.

The dynamics of learning evolve through the interaction of different learning processes occurring at different levels in the organization. While, in general the individual level is the receptor of the organization to the environment, knowledge of the organization is built on and incorporated into a supra-individual structure which is deeply involved in transferring knowledge within the organization. As the external environment of the organization specifies the action-outcome relationships available for learning, characteristics of the environment affect the dynamics of organizational learning and make environments demanding in different ways. Here, the comprehensibility of an environment for the organization is essentially connected to its degree of complexity. Environmental complexity not only depends on the number of its elements but, more importantly, on the interactions between these different elements.[228]

March (1991) pointed out that, with regard to mutual learning, fast learning of the individuals can often harm organizations. Diversity of beliefs is not a criterion for good learning performance per se, but an overly rapid convergence on similar mindsets can rule out valuable beliefs prematurely. Path dependence in the learning system is defined as a homogenous mindset within the organization which remains stable while better solutions are still available. It is therefore clear that in a simple environment fast learning in systems of mutual learning aggravates path dependence. While March's (1991) experiments differentiated between beneficial and detrimental conditions in processes of mutual learning, they did not allow any conclusion with respect to the effects of increasing environmental complexity. With the first experiment in this chapter, we therefore aim at answering the question, how environmental complexity impacts on organizational performance in the different learning regimes.

March (1991) continued his inquiries by adding another process into his model, personnel turnover. Replacing established organizational members with new members who have random beliefs about the environment for the system essentially is a source of variation. We think, in agreement with Hanaki & Owan (2010) and Lazer &

[228] For the relevant environmental characteristics see chapter 2.3.

Friedman (2007), that variation in systems of mutual learning is instead added by the ability of the individuals to acquire new knowledge as a process of learning from experience. Our second experiment in this chapter, therefore, aims to discover the effects of introducing experience-based individual learning into a system of mutual learning situated in complex environments.

6.3.2 Model Settings

In this chapter, we explicate how we specified the integrated learning model for experimental usage. In the model configuration we explained the basic specification of the model with respect to its parameters and their ranges. Here, we delineate how these parameters are set for the first set of experiments.

Our independent variables encompass the parameters which specify the organizational environment as well as the parameters which define the learning speed of the organizational learning processes. In this chapter, our focus is on exploring the model behavior in differently complex environments. In order to acquire a suitable size of the search space,[229] we specified the number of dimensions of the NK landscape in relation to the number of agents who walk the problem landscape.[230] While the size of the organization was set to 50 members (plus the code), N was set to 15. The complexity of the learning problem is then scaled by varying the parameter K. The parameter range for K ranges from 0, which corresponds to a simple environment without any interactions and only one optimum, to $N-1$ or maximum complexity where the performance of one belief-set offers no guidance as to the value of neighboring belief-sets. A change of one belief dimension in this landscape changes the performance contribution of every other dimension (Lazer & Friedman, 2007:674). The behavior of the model should be compared for all types of environments, from simple to highly complex environments. A highly complex environment imposes a great challenge on organizational learning but cannot be equated with an environment without any performance correlation between neighboring points in the landscape. In such a chaotic environment, the results of learning simply become a product of

[229] On the size of search spaces, see also Michalewicz & Fogel (2004:11).

[230] See chapter 6.1.2.

chance. We therefore specify a highly complex environment as one involving a high but not the highest possible degree of interdependence between environmental dimensions. In an environment of $N = 15$ and $K = 10$, several hundred of the 32768 possible solutions are local optima, confronting the organization and its members with many potential competency traps. A moderately complex environment, as we defined it in which $K = 3$, exhibits only one tenth of the number of local optima of the highly complex environment.[231]

Variable	**Parameter**	**Experimental setting**
Environmental complexity	K	0 (simple); 3 (moderately complex); 10 (highly complex)
Speed of learning from the code	p_a	0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9
Speed of learning by the code	p_c	0.1; 0.5; 0.9
Speed of individual learning	p_{expl}	0.0 (without ind. learning) 0.1; 0.9

Table 9: Parameters used in the experiments on complex environments and their experimental settings

The experimental settings for the parameters of learning speed in our first experiment on fast and slow learning in differently complex environments explore a similar range of learning regimes as did the original model of March (1991) to enable us to compare the results. As, in the first step, we explore the behavior of a model of mere mutual learning in complex conditions, the speed of the variation inducing learning process, individual learning (p_{expl}) is set to 0.

[231] For the exact figures concerning the number of local optima in the specified NK spaces, see Appendix C. The simulation runs in every experiment are conducted on different NK spaces to account for the variance in the number of local optima between spaces of similar configuration.

For our second step, in which we introduce individual learning into the model, we narrow down the experimental settings for the rates of learning to represent the extreme cases of beneficial and detrimental learning conditions. Fast learning *from* the code combined with slow learning *by* the code proved to result in the worst organizational performance. On the other hand, beneficial learning conditions involve slow socialization combined with a code which quickly realizes the potential of beliefs of the organizational members. Based on these learning regimes in this step, we explore the effects of differently complex environments on the integrated model with combined mutual and individual learning.

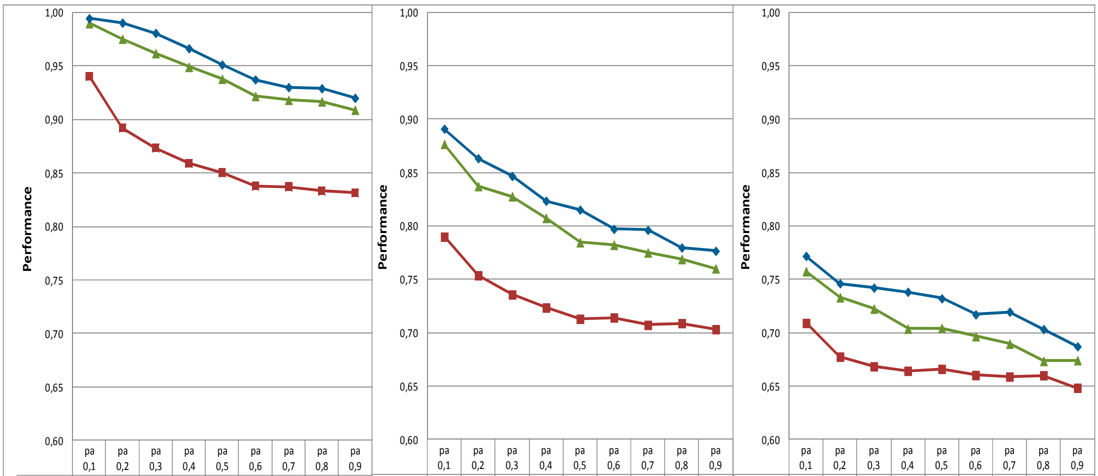
6.3.3 Results

The following chapters present the model's results in different regimes of environmental complexity. Since we employ the building block approach of increasing model intricacy, the experimental results are presented in the order of the conducted experiments. First, we point out the results of mutual learning in environments of different complexity. In the next step, we account for the results of the integrated model in which mutual learning is accompanied by competence-enhancing learning of the organizational members.

6.3.3.1 Fast and Slow Learning and the Impact of Environmental Complexity

In March (1991), the organization is confronted with an environment which is not subject to interaction effects between its dimensions. Here, the organizational learning success is calculated as a percentage of the dimensions of reality that are correctly represented in the organizational code. In our environment, the performance value of the organizational code is determined by the performance contributions of its different dimensions which represent a given point in the NK landscape. Interaction effects between the different environmental dimensions determine the complexity with which the organization is confronted when searching for a good belief-set. Environments which feature more interaction effects between dimensions consequently complicate the search task for the organization and involve a higher number of local optima or competency traps. We already presented the results of our model for organizational learning in a simple environment ($K = 0$).[232]

We now compare learning in a simple environment with learning in medium to highly complex environments. For this comparison, we chose to simulate organizational learning for all the learning regimes involved in the original March (1991) setting. Slow, medium, and fast learning *by* the code is combined with nine different speeds for learning *from* the code ranging from fast to slow so that we can directly compare with the performance of the organization in a simple environment. The following graphic shows the results of the different learning regimes in simple, medium and highly complex environments. For each data point the simulation was run 600 times.



	pa 0,1	pa 0,2	pa 0,3	pa 0,4	pa 0,5	pa 0,6	pa 0,7	pa 0,8	pa 0,9
Pc=0,1	0,940	0,892	0,873	0,859	0,850	0,838	0,837	0,833	0,832
Pc=0,5	0,990	0,975	0,962	0,949	0,938	0,922	0,918	0,917	0,909
Pc=0,9	0,994	0,990	0,981	0,966	0,951	0,937	0,930	0,929	0,920

	pa 0,1	pa 0,2	pa 0,3	pa 0,4	pa 0,5	pa 0,6	pa 0,7	pa 0,8	pa 0,9
Pc=0,1	0,790	0,754	0,736	0,724	0,713	0,714	0,707	0,709	0,703
Pc=0,5	0,877	0,837	0,828	0,807	0,785	0,782	0,775	0,769	0,760
Pc=0,9	0,891	0,863	0,847	0,823	0,815	0,797	0,796	0,780	0,777

	pa 0,1	pa 0,2	pa 0,3	pa 0,4	pa 0,5	pa 0,6	pa 0,7	pa 0,8	pa 0,9
Pc=0,1	0,709	0,678	0,669	0,664	0,666	0,660	0,659	0,660	0,648
Pc=0,5	0,758	0,733	0,723	0,704	0,704	0,697	0,690	0,674	0,674
Pc=0,9	0,772	0,746	0,742	0,738	0,732	0,717	0,720	0,703	0,687

Figure 26: Differences between the learning regimes in K0, K3 and K10 environments (from left to right)

From Figure 26 we may deduce that complexity considerably moderates the significance of the emerging organizational lock-in. While an organization with beneficial learning conditions in a simple environment comes close to the optimum solution, as expected, performance drops within complex environments.

[232] See chapter 6.2.1.

Interestingly, complexity also seems to influence the differences between the three learning regimes of the code (0.1; 0.5; 0.9). With increasing complexity, these become less pronounced, especially when combined with fast learning from the code of the organizational members. Even a highly intelligent code which incorporates beliefs of the organizational members quickly ($p_c = 0.9$) becomes less able to compensate increasing environmental complexity. A similar tendency with increasing complexity can be identified for the regimes of learning from the code (p_a). In a medium complex environment ($K = 3$), at first the impact of the speed of learning from the code gets more pronounced, especially for a fast learning code. In highly complex environments ($K = 10$), this influence again declines flattening the gradient of the curves. The speed with which the organizational members learn from the code becomes less meaningful for the organization.

Environmental complexity is bound to significantly affect the impact of different learning conditions in organizations. In simple environments, the intelligence of the code (learning *by* the code) in particular influences the organizational learning result. In moderately complex environments, the significance of the speed of learning *from* the code seems to increase. Prolonging diversity in the organization[233] here seems to be more beneficial. In highly complex environments, the differences between the different regimes of both learning processes (learning *from* the code and learning *by* the code) become less conspicuous. A similar tendency is also found in models of organizational design. If environments become overly complex, performance differences between different organizational designs vanish (Siggelkow & Rivkin, 2005).

The different learning regimes also impact the time it takes the organization to converge on a homogeneous belief-set. The following figure shows a comparison of history charts for different learning regimes in differently complex environments. It also provides a more detailed insight into the organizational learning dynamics.

233 Remember that in this configuration no new variation is introduced into the model during a run ($p_{expl} = 0.0$).

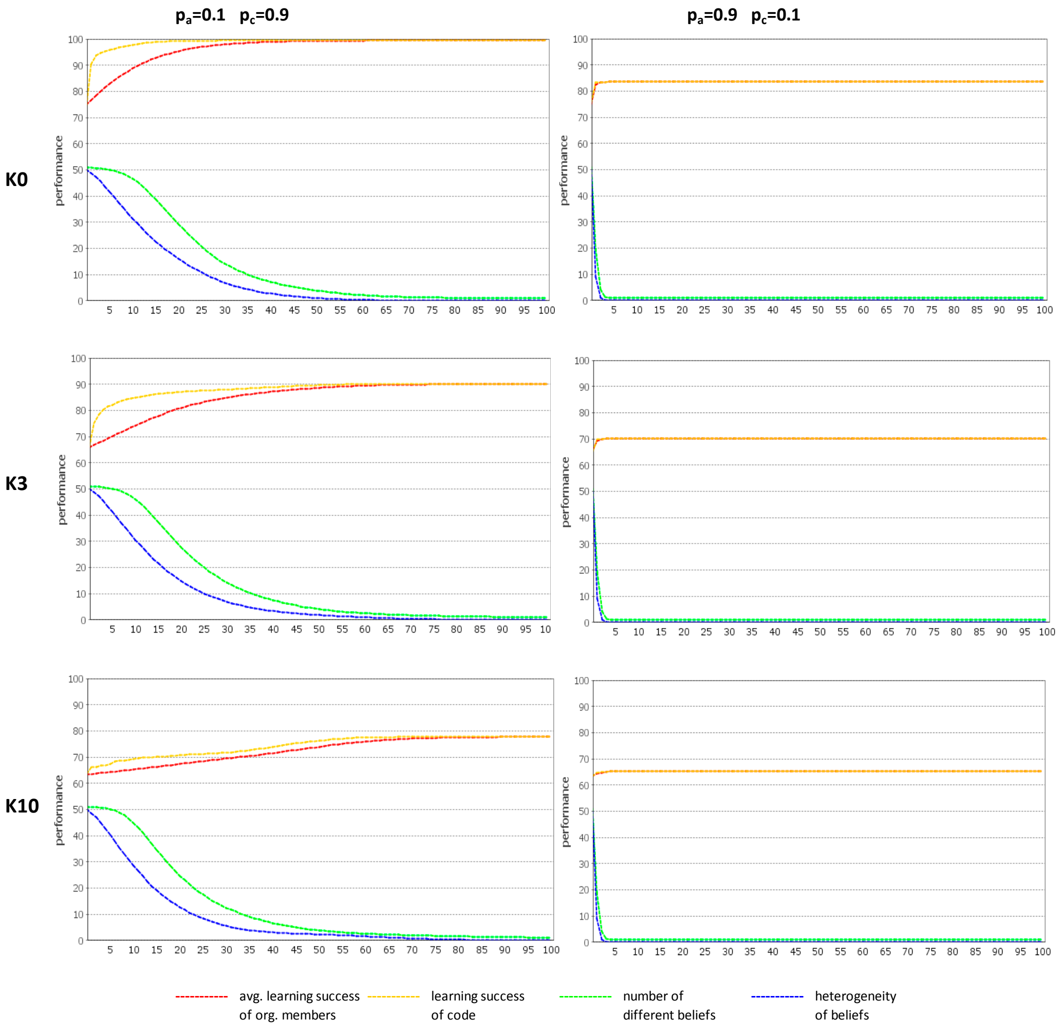


Figure 27: Mutual learning in differently complex environments with beneficial (p_a=0.1; p_c=0.9) and detrimental learning regime (p_a=0.9; p_c=0.1)[234]

Similar to the preceding figure, Figure 27 shows that the significance of the lock-in increases with complexity. This is the case for all learning conditions but becomes less significant in highly complex environments. What we can derive from Figure 27 is that the performance differences between good and detrimental learning conditions are directly related to the time of convergence on a homogenous belief-set.

[234] Learning by the code is simulated as the code approaching the weighted belief-set of the better performers as done in March (1991). See chapter 5.3.1 on the different logics employed for learning by the code in models of mutual learning.

In detrimental learning conditions, the number of different belief-sets in the organization (green curve) declines almost instantly and the heterogeneity of the remaining different beliefs during this decline similarly is very low (blue curve). In beneficial learning regimes, the organization preserves a higher number of different beliefs for a longer amount of time. In simple and moderately complex environments, the intelligent code is able to profit from this diversity by finding better representations of the organizational environment (yellow curve). We recognize that it increases and distributes its knowledge in the organization. This shows in the slower increase of the average performance of the individuals in the organization (red curve). In highly complex environments, on the other hand, the increase in code knowledge is much slower and less steep. Even a very intelligent code in a highly diverse organization is not able to find good solutions quickly; it is strongly affected by the environmental complexity. Even a longer process of convergence cannot make up for the detrimental effects of environmental complexity on the significance of the lock-in.

Considering the outcome of one run with beneficial learning conditions in a highly complex environment makes these dynamics more obvious. Complexity affects the ability of the system to improve. Figure 28 shows in greater detail that in a highly complex environment the organization improves only slightly even in beneficial learning conditions and, as in this case, might meanwhile also be able to damage the average performance of the organizational members.

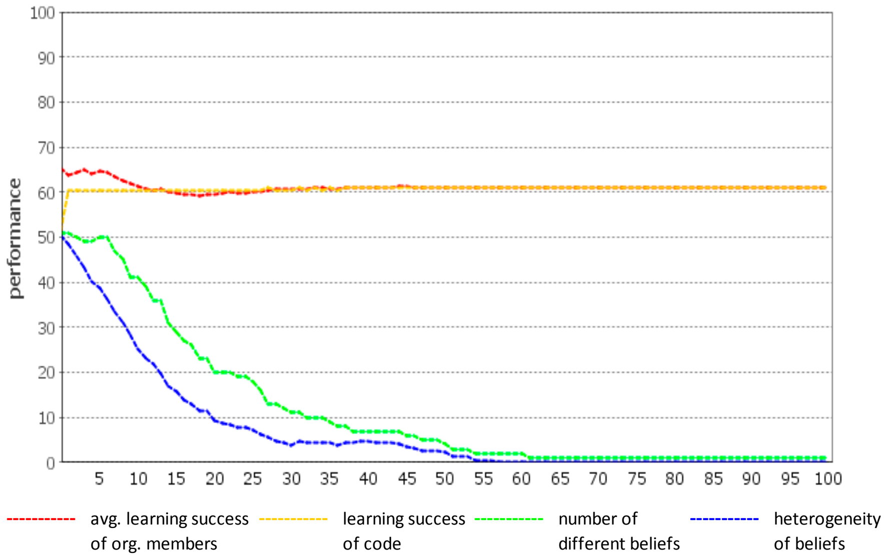


Figure 28: Example run in a highly complex environment with beneficial learning regime (p_a=0.1; p_c=0.9)

6.3.3.2 Individual and Mutual Learning and the Impact of Environmental Complexity

In the next step, we integrate individual competence-enhancing learning into the model and move away from the original configuration of organizational learning of March (1991) which did not involve individuals learning from their own experience but merely from the experience of others. March (1991) and similarly Fang, Lee, & Schilling (2010) considered another process which brings variation into the organization: personnel turnover. We compare our results to the results achieved in these models with personnel turnover. As the competence-enhancing learning of the individuals incorporates new belief-sets into the organization, in the following section, we often refer to this learning process as exploration therewith hinting at the function it fulfills at the organizational level.[235]

In general, incorporating additional variation during organizational learning gives the organization a greater diversity of belief-sets to select from and, consequently,

[235] For a more detailed explanation of the learning processes and their functions for the different levels in organizations, see chapter 4.3.

improves the learning result. In a simple environment as shown in Figure 29, exploration of the individuals enables the organization to always arrive at the global optimum. A simple environment even renders it possible for the individual to do so in isolation without the mutual learning process.[236] The organizational embedding of individuals simply enables a faster distribution of good solutions so that the organization finds the efficient representation of the environment earlier than in the case of isolated individual learning.

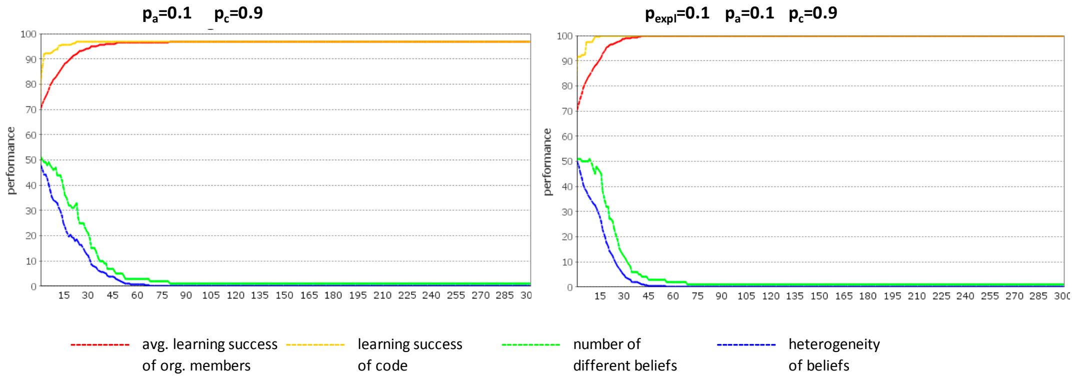


Figure 29: Example run in a simple environment (K=0) with beneficial learning conditions without and with individual learning

Fast and slow learning have a significant impact on the process in a simple environment. From Figure 30 (first row) we see that, with detrimental learning conditions, in which the code learns slowly from the individuals but the individuals learn quickly from the code, the process looses much of its intelligence. The organization eventually arrives at the global optimum, but the quick socialization of the individuals to the often inferior beliefs of the code distracts the individuals from their learning path. From the very beginning of the learning process the variety of beliefs in the organization disappears quickly diminishing the learning opportunities of the organizational code. The time to reach a convergence of beliefs is greatly prolonged without any beneficial effects for the organization.[237]

[236] This is a consequence of a local search process in a landscape with only one optimum, see chapter 6.2.2.

[237] As in a simple environment the organization always reaches the global optimum we cannot assume it to be a state of path dependence.

Proceeding into complex environments (Figure 30, second and third row), we realize that environmental complexity even in beneficial learning conditions leads to path dependence. Here, the individuals in the organization are confronted with local optima in the problem landscape. Even if learning from the beliefs of others (as is the case when the individuals learn from the code) enables the individuals to break free from local optima in the landscape, this does not suffice to lead the organization to an efficient belief-set.

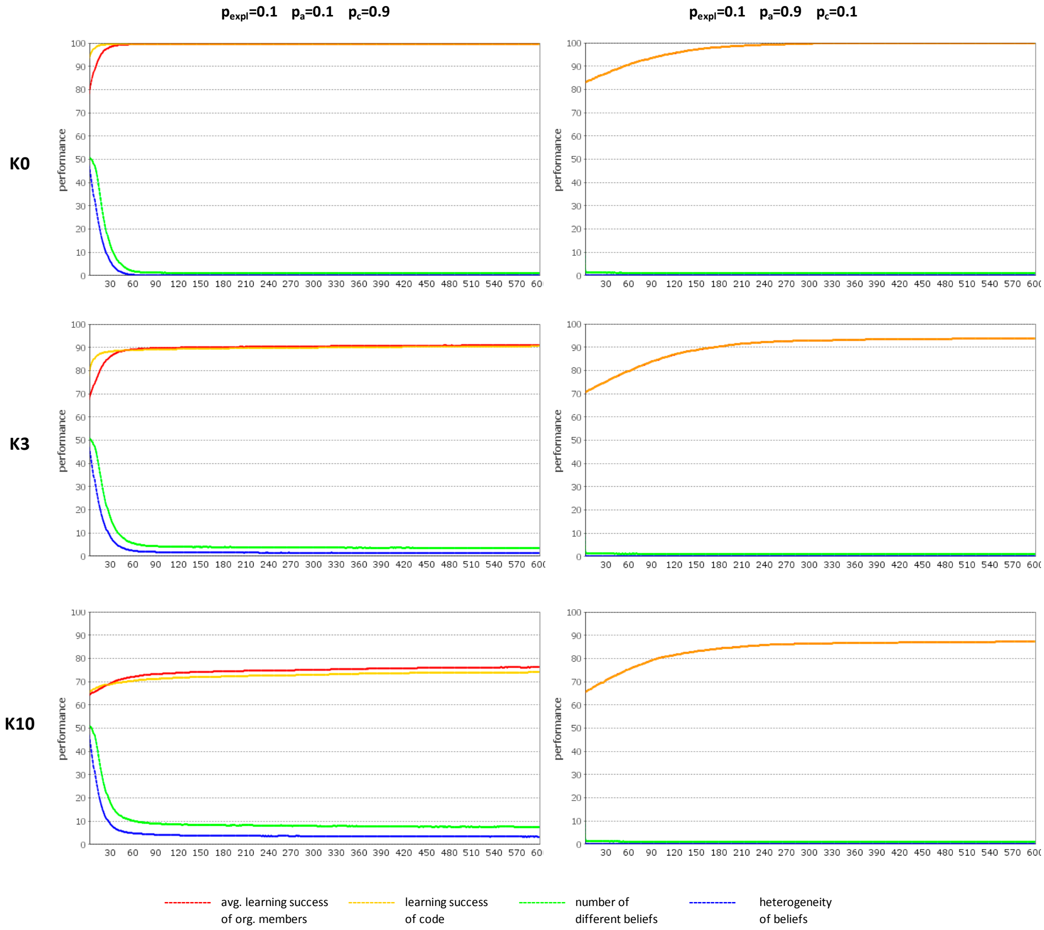


Figure 30: Beneficial and detrimental learning conditions in differently complex environments with individual learning

Before we delve deeper into the effects of environmental complexity in a model with individual learning, we refer to an unintended effect of the logic March employed for the code learning process which surfaces when the model is taken into a complex environment. The organization shows a fluctuating behavior as can be seen in the above figure. In complex environments, on average a certain amount of different but similar belief-sets remain in the organization (see second and third row, blue and green curves). Single model runs show that in this configuration, the organization oscillates between different beliefs. This effect is due to the coupling between the process of learning by the code and individual learning. Because the number of those better-performing individuals identified by the code for learning is flexible and connected to code performance, the system experiences an interaction effect between the size of the group of better performers and the heterogeneity of its beliefs. If the heterogeneity falls below a certain level, the system becomes unable to identify good solutions while the individuals keep on trying to incorporate them due to their explorative activity. This effect can be controlled by fixing the size of the group of better performers which the code identifies for learning.[238] All preceding experiments are therefore conducted with a fixed size of this elite group. The behavior of the model with the parameter setting the size of the elite ($numBetterPerf$) was subject to an intense evaluation with different parameter values to assess the exerted influence. In general, these experiments show interesting effects concerning an intensification or diversification of the search process due to the size of the elite but do not directly correspond to the research focus of this work. Readers are therefore referred to Appendix G for more detailed information. Based on the evaluation of the influence of the parameter, we set the size of the group that the code identifies for learning to a medium value with which the code considers the beliefs of the best 10% of performers.[239] This seems to reproduce March's (1991) results best without being subject to the oscillating tendencies of the original configuration.

We have already demonstrated that complexity affects the performance achieved by the organization during learning. In simple environments, competence-enhancing learning of the individuals can protect the organization from falling prey to path dependence. In complex environments, while individual exploration significantly increases organizational intelligence, the interaction of exploration and mutual

[238] A related approach can be found in Rodan (2005). Here, the size of the group of superior performers can be determined by a stringency parameter.

[239] The parameter $numBetterPerf$ is set to 5. In each step of learning, the code selects the five best performing individuals in the organization, aggregates their beliefs to a majority view and learns from this majority view according to p_c.

learning does not suffice to enable the organization to always find efficient belief-sets. Besides these obvious effects on the organizational learning results, we note that exploration when compared to learning regimes without exploration, also impacts the time to convergence.

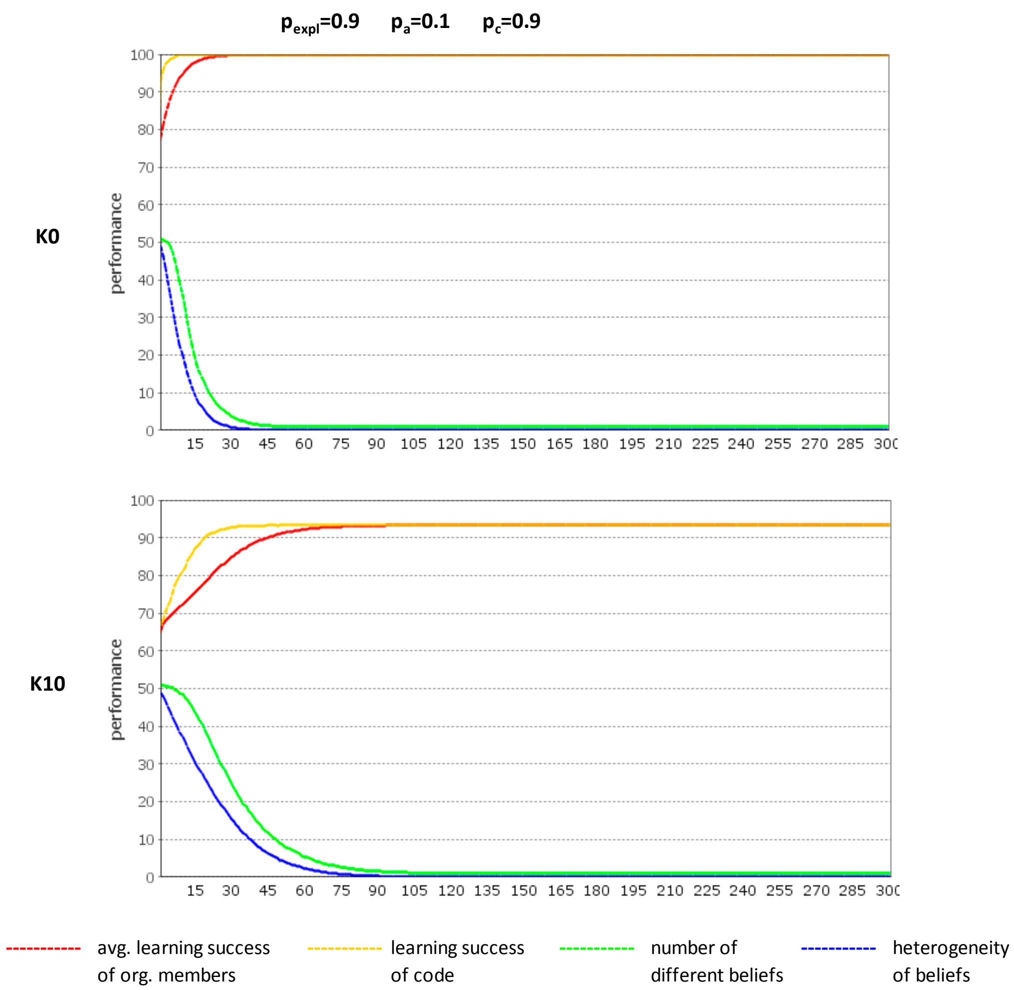


Figure 31: Beneficial learning conditions in simple and complex environments with individual learning

With increasing complexity the time it takes the organization to settle on a similar belief-set increases. This seems to be a direct effect of the variety introduced by the explorative activity of the individuals. The individual exploration activities disturb the socialization process and similarly confront the organizational code with new learning opportunities in each time step. For increasing complexity, we could have forecasted two different effects. On the one hand the landscape involves more competency traps which would point to a faster lock-in of organization and agents. On the other hand, learning is complicated by more interaction effects which involve larger alterations of performance scores due to the search activities of the agents which again lead to more distractions in learning by the code. That the time to convergence in Figure 31 increases with increasing complexity makes an interesting point for the intelligence of organizations resulting especially from the interaction of individual and mutual learning processes. We explain this in greater detail in the remaining chapter.

In the following section, we compare how individual exploration impacts organizational learning in beneficial or detrimental learning regimes. In general, individual exploration improves the learning result (see Figure 32).

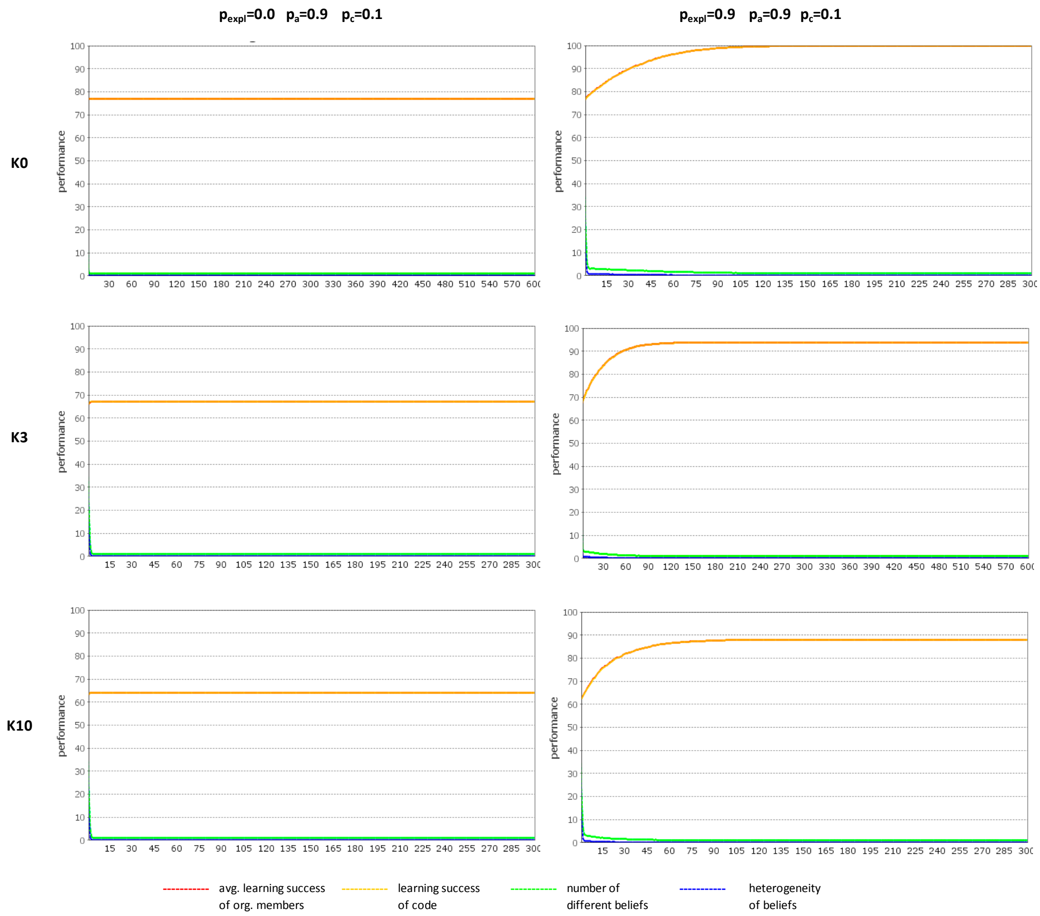


Figure 32: Detrimental learning conditions in differently complex environments without and with individual learning

In detrimental learning conditions, the organization quickly loses its internal variety of beliefs. If we view the mechanism of mutual learning as a constant exchange of beliefs between the organizational members moderated by the code, in detrimental conditions this mechanism is weak, it impacts only very briefly on a large variety of beliefs in the beginning of the learning process. In good learning conditions, on the other hand, the exchange of beliefs is prolonged. Therefore, in each learning regime individual exploration impacts based on different amounts of belief variety remaining in the system in each time step.

Let us first consider the interaction for simple environments. The dynamics of convergence result from the belief variety present in the system. In a detrimental learning regime, we experience a rapid initial decline of the belief variety followed by a long climb to the optimum in the NK landscape. The environment is simple enough for even an individual in isolation to reach the optimum; it does not require the intelligence of organizations. Actually, the process with detrimental learning conditions greatly resembles the one with isolated individual exploration. The relevant criterion is how the beliefs in the organization are distributed. In a detrimental learning regime, the optimum has to be found from few almost identical belief-sets.

Compare this situation to the one in beneficial learning conditions. Here, individual exploration can impact based on a significant belief variety. The initial decline in belief variety is slow so that the belief variety forms a broad basis for individual exploration activities. Here, the organization searches its environment starting from multiple positions in NK and, consequently, arrives at the global optimum faster than the organization with detrimental learning conditions. The dynamics result from how pronounced the mechanisms of learning, either mutual learning or experience-based learning, appear in the model.

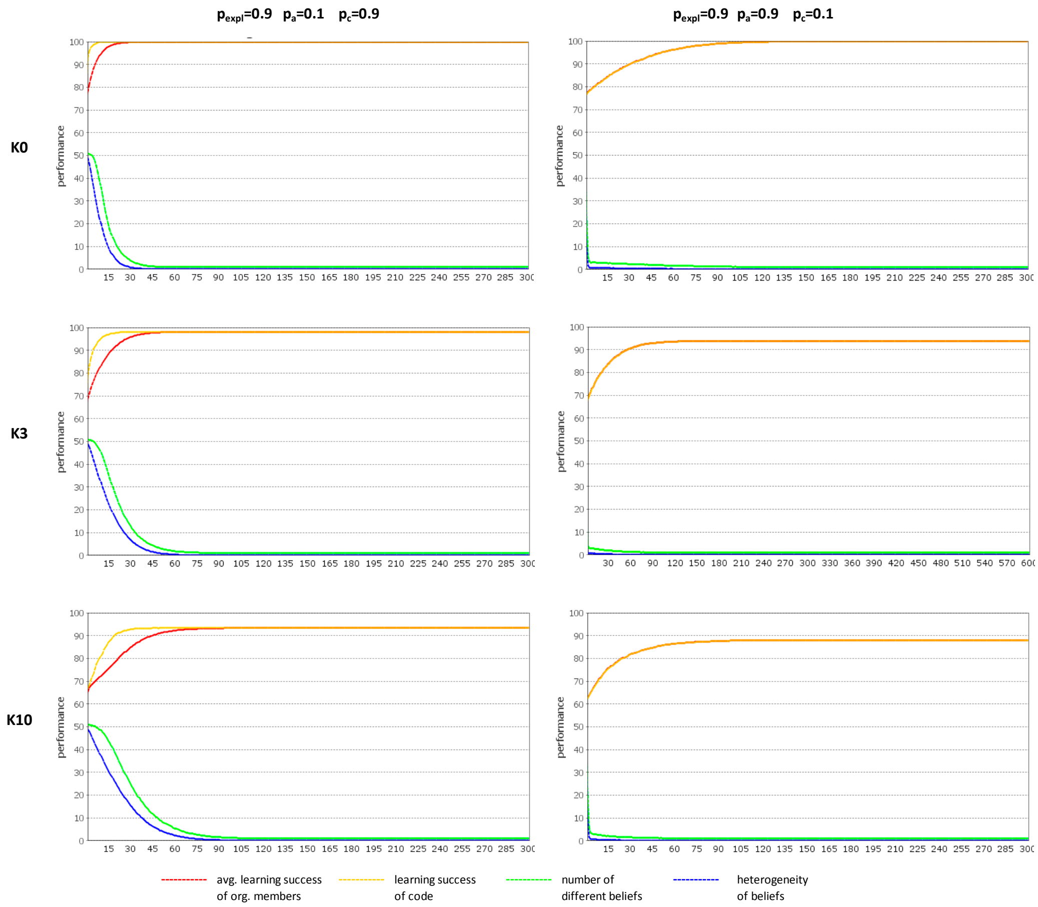


Figure 33: Beneficial and detrimental learning conditions in differently complex environments with individual learning

This basic interaction is further moderated by environmental complexity. We have already shown in Figure 32 that convergence time is also impacted by environmental complexity. While time to convergence is, in general, longer in detrimental learning conditions with exploration, the impact of complexity differs from that in beneficial learning conditions.

In beneficial learning regimes, time to convergence increases with increasing complexity, in detrimental regimes it declines. With relation to the identified dynamics resulting from the interaction of both learning processes, this leads us to the following conclusion. In beneficial learning regimes the mechanism of mutual learning, reflected in the exchange of beliefs, is much more pronounced. Here, complexity distracts organization and agents from their learning paths and prolongs the learning process. In a detrimental learning regime, the mechanism of experience-based search prevails, while the mutual learning mechanism only acts based on small changes in an already quite homogenous belief-set. Experience-based learning confronted with increasing complexity has the tendency to get stuck faster as the number of competency traps in the environment increases.

The findings above presented are further supported by the following investigation. In this scenario, we decouple organizational and individual level maximally thereby increasing the time that the mutual learning process will impact with maximum belief variety ($p_a = 0.1;\ p_c = 0.1$). This configuration we test for two different levels of individual exploration ($p_{expl} = 0.1;\ 0.9$).

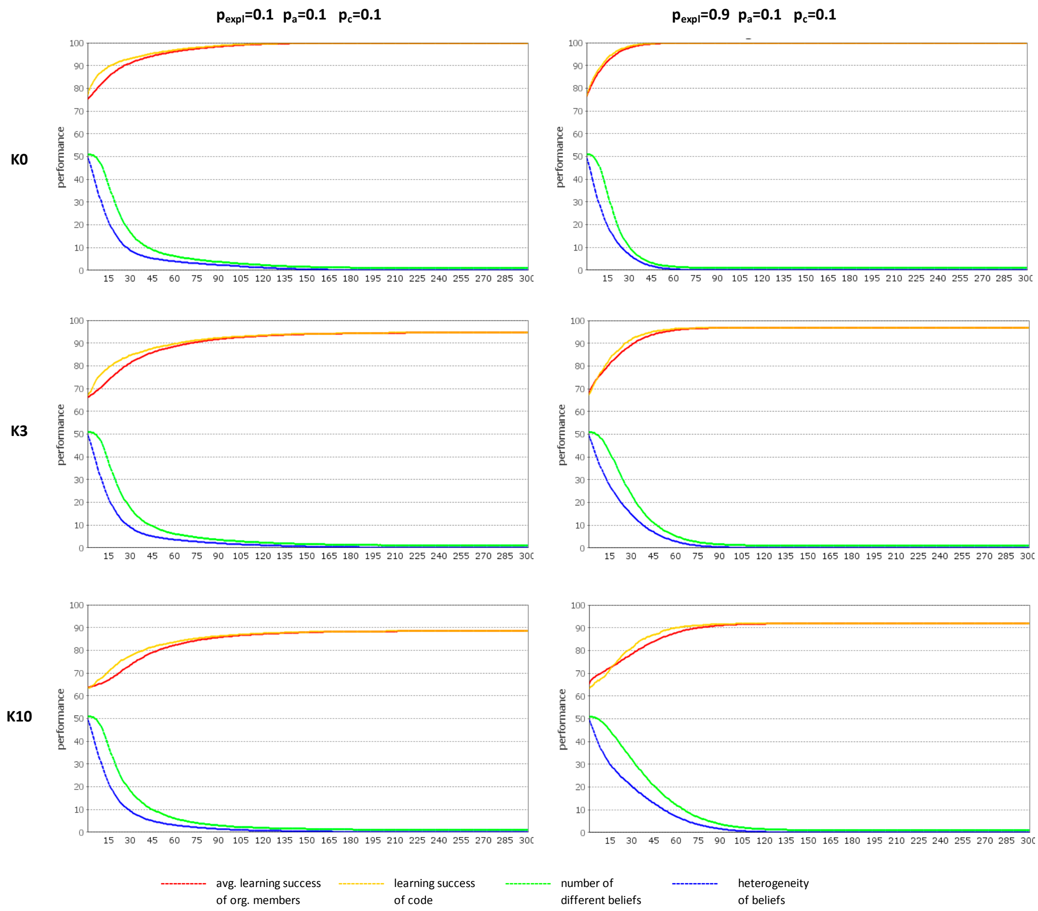


Figure 34: Equal learning conditions in differently complex environments with different rates of individual learning

Two effects can be recognized. In a low exploration regime, we experience a longer time to convergence which is accompanied by a steeper decline of belief variety in the system. In a high exploration regime, the time to convergence is shorter, but the organization during this decline acts based on a higher belief variety. The low exploration regime, moreover, shows a slightly reduced time to convergence with increasing environmental complexity, the steeper decline of knowledge variety in the path towards convergence leads to the dominance of the local search mechanism which gets stuck easily in the increasing number of competency traps. In the high exploration regimes, an increase in the time to convergence can be seen which shows the previously described effect of a more pronounced mutual learning mechanism which acts on a greater variety of beliefs. Organizations with a high exploration regime, in general, are better prepared for coping with their environment. Even if individual exploration significantly improves system performance in detrimental learning conditions, it is especially valuable if it impacts while there is still a higher belief variety in the system. Here, its effect of discovering the potential of the different solutions can become particularly beneficial for the organization.

In the previous chapter, we pointed out that complexity affects the ability of the system to improve. Adding individual exploration to the picture introduced an additional dynamic into the organization. Exploration incorporates variety into the organization but not without restraints as do, for example, processes of personnel turnover (March, 1991; Fang, Lee, & Schilling, 2010). The interaction of mutual learning and local search dynamics, in general, enables organizations to cope astonishingly well with complexity in their environment. But the unfolding dynamic in the face of environmental complexity strongly depends on how the two mechanisms inside the organization interact.

The variety-introducing mechanism of individual learning differs from that of personnel turnover in two respects. First, turnover has a negative effect on average performance of the individuals in the organization, as random new knowledge is introduced (March, 1991:78). Second, turnover preserves heterogeneity in the organization indefinitely, in a model with turnover the organization does not converge on one belief-set eventually (Fang, Lee, & Schilling, 2010:635). The dynamics of individual learning therefore differ significantly from the ones produced by personnel turnover. March found that good learning regimes (with a low socialization rate) are generally affected negatively by turnover while the positive effect of turnover surfaces in detrimental learning conditions with high socialization rates and only at medium amounts of turnover. March (1991:78) refers to a trade-off between learning rate and turnover rate. Slow learning and rapid turnover result in inadequate exploitation. High learning rates imply an already high exploitative tendency in the organization and therefore require at least moderate amounts of turnover.[240]

In our case, individual exploration holds promises for both beneficial and detrimental learning conditions. Individual learning also introduces variety into the system but this variety is not completely detached from the former knowledge state of the individuals. Since individual learning improves the knowledge state of single individuals, it always increases the average performance of the organizational members, but it shows its own path-dependent tendencies (Castaldi & Dosi, 2004:3). Therefore, on an organizational level, its benefits decrease with declining variety during the organizational learning process. Systems which command a high diversity of beliefs are able to profit more from individual learning. They search a larger part of the landscape and discover the potential of dissimilar solutions. Declining variety in the organization reduces the effectiveness of individual exploration. The interaction of both learning processes also shows beneficial contributions with respect to approaching a valid belief-set. Starting from numerous different positions coupled with individual learning to quickly evaluate their potential leads to a quick achievement of often astonishingly intelligent results.

To this process, complexity resulting from interaction effects between environmental dimensions,[241] adds its own significant influence. The effects of increasing complexity depend on how the different learning processes interact. With a dominant local search mechanism of individual learning and mutual learning acting on almost similar beliefs, increasing complexity leads to an earlier lock-in. Increasing complexity for systems with a stronger mutual learning mechanism based on a higher belief variety, increases time to lock-in as complexity distracts the exchange of beliefs.

[240] Fang, Lee, & Schilling (2010) do not deal with the effects of personnel turnover in a stable environment; they test it in a turbulent environment. We come to this in chapter 6.4.3.2.

[241] Here, we do not refer to merely an increased number of dimensions like for example Miller, Zhao, & Calantone (2006).

Since belief variety and the effectiveness of individual learning interact, timing during organizational learning seems to play a major role. In chapter 6.4, we investigate how the frequency and scope of change influence the described dynamics.

6.4 Second Set of Experiments: Path-Dependent Organizational Learning in a Turbulent Environment

In our second set of experiments, we build on the results of implementing environmental complexity and further add environmental turbulence to our model. Environmental turbulence will be considered as differing in the scope of change as well as its frequency so that different regimes of turbulence can be tested. We follow a similar experimental outline as in the chapter on the effects of environmental complexity and start by exploring environmental turbulence in a model of merely mutual learning. In a second step, we append individual competence-enhancing learning to examine its effects for organizational adaptability in changing environments.

6.4.1 Recapitulation: Problem Outline

Exogenous environmental change at the same time complicates learning and makes adaptation indispensable (Weick 1979). We pointed out in chapter 6.3 that belief variety and the effectiveness of exploration interact and explored several dynamics resulting from this interaction. The results suggest that in organizational learning the timing of change is important. This is not merely the case for change based on internal mechanisms of the organization resulting from its processes of learning but also for change impacting on organizational learning from outside the organization's boundaries. Consequently, when and also how an organizational environment changes is bound to have a significant effect on the learning process.

Organizational learning involves a convergence of beliefs. The underlying logic of the research presented here is that it is by this process that the organization realizes its learning potential. Even if organizations learn based on feedback from their environments, due to this convergence process their adaptability during learning declines. This raises the question whether, in a changing environment, long run variety or fast convergence of beliefs proves beneficial for the organization (Lazer & Friedman, 2007:688-689). We have already shown in the preceding chapter that the configuration of the learning processes affects the dynamics of internal variety and convergence. We now ask how these configurations perform in turbulent environments.

Our argument so far shows that merely invoking environmental change as a disturbance in the organizational environment impacting continuously (with a certain scope in each time step of the simulation) does not provide the necessary differentiation to deal with this question. To refine these research results (March, 1991; Fang, Lee, & Schilling, 2010[242]; Hanaki & Owan, 2010), we introduce a more specific characterization of environmental change. Environmental change differs according to its scope and its frequency (Siggelkow & Rivkin, 2005; Kim & Rhee, 2009). Similar to chapter 6.3, we increase model intricacy step-wise in order to understand the model's dynamic. Whereas our first experiment inquiring into the effects of change scope and frequency involves merely mutual learning of individuals and organization, in our next step, we again append learning of the individuals in the organization. We believe that, particularly in a changing environment, experience-based learning of the organizational members as a variation-increasing mechanism is of special importance.

6.4.2 Model Settings

We already specified the learning parameters and environmental complexity for our first set of experiments.[243] In this chapter, we build on the results achieved in chapter 6.3 and inquire into the effects of two additional independent variables, the frequency and scope of environmental change. Although we tested environmental turbulence for a broad range of learning parameters and complexity,[244] in the following, we often

[242] Fang, Lee, & Schilling (2010) make the assumption that the time scale for environmental change is longer than that for learning which is why we consider them part of the above cited approaches.

[243] See chapter 6.3.2.

[244] See chapter 6.5 on model robustness.

focus the reporting of results on moderately complex environments and the learning conditions producing the most different organizational performance. Fast and slow learning conditions will be tested in complex environments which are subject to different settings of environmental turbulence. The following table shows the different environmental scenarios.

Regimes of environmental turbulence	Low frequency of change	High frequency of change
Low scope of change	Regular regime [τ =0.8; x=50, 100]	Gradual regime [τ =0.8; x=5]
High scope of change	Disruptive regime [τ =0.2; x=50, 100]	Hyper-turbulent regime [τ =0.2; x=5]

Table 10: Parameter configurations for the scenarios of environmental turbulence

The parameter τ specifies the impact of the environmental change. A high figure ($0 \leq \tau \leq 1$) denotes that after a change a high proportion of the value associated with a specific setting of an environmental dimension stays unchanged and thus indicates a change of low scope. Past and present configurations of the environment, in this case, are closely related. A small τ, on the other hand, points to a significant change of the value attached to different belief configurations. The correlation between past and present is small. The parameter x expresses the frequency of change. Every x ticks the organizational environment is subject to change of the specified scope.[245]

We distinguish between four scenarios resulting from high and low combinations of the two parameters.[246] In the following section, we differentiate between infrequent change of low scope which we call a regular change regime and infrequent change of

[245] For a more detailed specification of the parameters τ and x see chapter 5.4.2.

[246] For a definition of the different scenarios see chapter 2.3.

high scope which, because of its rare occurrence but significant intensity, is referred to as disruptive change. A gradual change environment corresponds to one which experiences frequent change but of low scope. Finally, environments which are subject to the most extreme form of change which impacts frequently and strongly, we call hyper-turbulent.

The specific settings of the parameter x result from the length of the organizational learning process. We explicitly wanted to create settings in which change impacts after the organization has converged on a homogenous mindset as well as settings in which the timescale for organizational learning is not greater than the one of environmental change. In this way, we are able to inquire into organizational behavior after the lock-in and to explore the effects of environmental change on the ongoing interaction between mutual and individual learning. Investigating change impacting every 5 ticks and every 50 ticks (or every 100 ticks respectively) in different regimes of learning enables us to inquire into the adaptability of the organization in various stages of the learning process.

In chapter 6.3 we reported four different dependent variables which reflected organizational learning behavior, the learning success of the code, the average learning success of the organizational members, the belief heterogeneity and the number of different solutions for each time step of the simulation. We proceed in this chapter in a similar way but as already indicated in chapter 5.4.1 have to account for the learning success of the code and the average learning success of the individuals not as a score normalized to the global maximum in the NK landscape but as an absolute value. Due to the perturbations of the NK landscape the global optimum experiences a regression to the mean which would otherwise confuse our assessment of the learning process.[247] The absolute value of the learning success in this set of experiments therefore reflects simply the value of the performance mapping:

$$F = \frac{\sum_{i=1}^{N} f_i(x_i)}{N}$$

Performance values in this chapter, as a consequence, still provide us with a measure how well an organization performed in relation to an organization in different settings

[247] For more detailed information on the effects of environmental turbulence on the performance values of the NK landscape, see Appendix H.

but they no longer indicate how well the organization performs in relation to how well it could perform (Ganco & Hoetker, 2008:12-13).[248]

6.4.3 Results

The following chapters present the model's results in different regimes of environmental turbulence. In line with the preceding chapters inquiring into environmental complexity, the results are presented in order of increasing model intricacy. The first experiment deals with different paces of mutual learning in the specified regimes of environmental turbulence. The second experiment is devoted to exploring the effects of adding constant variation to the system as a result of individual experience-based learning.

6.4.3.1 Fast and Slow Learning and the Impact of Environmental Turbulence

It is intuitively intelligible that turbulence of the organizational environment affects organizational learning. March (1991) particularized the relationship between learning and environmental turbulence in the following way:

> *"Since learning processes involve lags in adjustment to changes, the contribution of learning to knowledge depends on the amount of turbulence in the environment."* March (1991:79)

While personnel turnover proved to be a mechanism which often harms the organization in stable environments, March (1991) shows its beneficial aspects in an environment in which every dimension changes continuously with a given probability. Without turnover, the organization experiences an initial increase in knowledge while there is still sufficient belief variety to cope with environmental change. March (1991:80) exemplifies that with declining belief heterogeneity in the organization the capabilities for change decrease. After convergence on a homogenous belief-set,

[248] Although Siggelkow & Rivkin (2005) test their different organizational designs in different environmental settings, they report the relative organizational performance. Since we want to assess the history of the adaptation process of the organization, their approach is not feasible for us.

environmental change continues to reduce organizational knowledge until finally it reflects a mere random guess concerning the state of the organizational environment. Environmental turbulence therefore strongly affects organizational learning. The learning ability of the organization is in turn dependent on its belief variety. As a result, the timing between organizational learning and the occurrence and strength of environmental change becomes important (Kim & Rhee, 2009). The development of the belief variety in the organization depends on the specified paces of learning from the code and by the code while the timing and impact of environmental change depends on the specified frequency and scope of change in the performance contributions of the environmental dimensions.

Figure 35 shows the basic characteristics of organizational learning in a simple environment which is subject to environmental change.

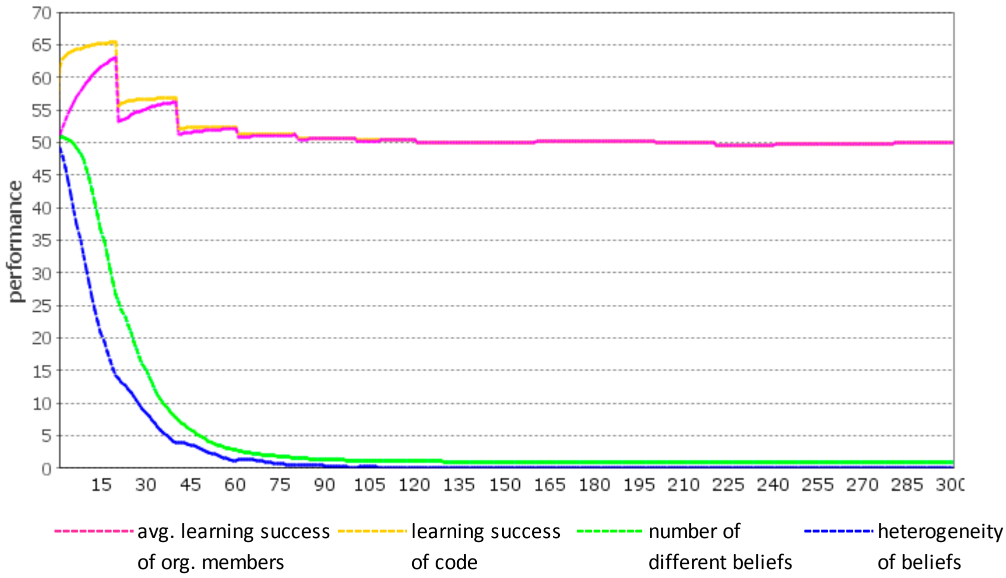


Figure 35: Mutual learning in a simple environment with turbulence (τ =0.2; x=20; p_a=0.1; p_c=0.9)

Without attending to the specific type of turbulence, we recognize the degrading of knowledge with every cycle of change. As presented in the chapter on environmental complexity, the chart reports the development of belief heterogeneity (blue) and the number of different solutions in the system (green). The learning success of the code (yellow) as well as the average individual learning success (magenta) in the organization, for the reasons specified in the model settings[249] are described as absolute performance values of the locations represented by the bit combination of the code and the average scores of the bit combinations inhabited by the individual agents in the NK landscape. We notice that, after an initial phase of improvement, organizational learning success becomes a mere product of chance. Organizational performance is decreased with every change in the environment until finally it becomes a random walk around a medium value in NK which, in essence, shows no adaptation or improvement. As before, the results on environmental turbulence will be presented in a similar way throughout this chapter.

Different environmental scenarios are bound to produce different organizational leaning histories. Figure 36 depicts example runs with beneficial learning conditions in a simple environment for the specified scenarios of environmental turbulence.

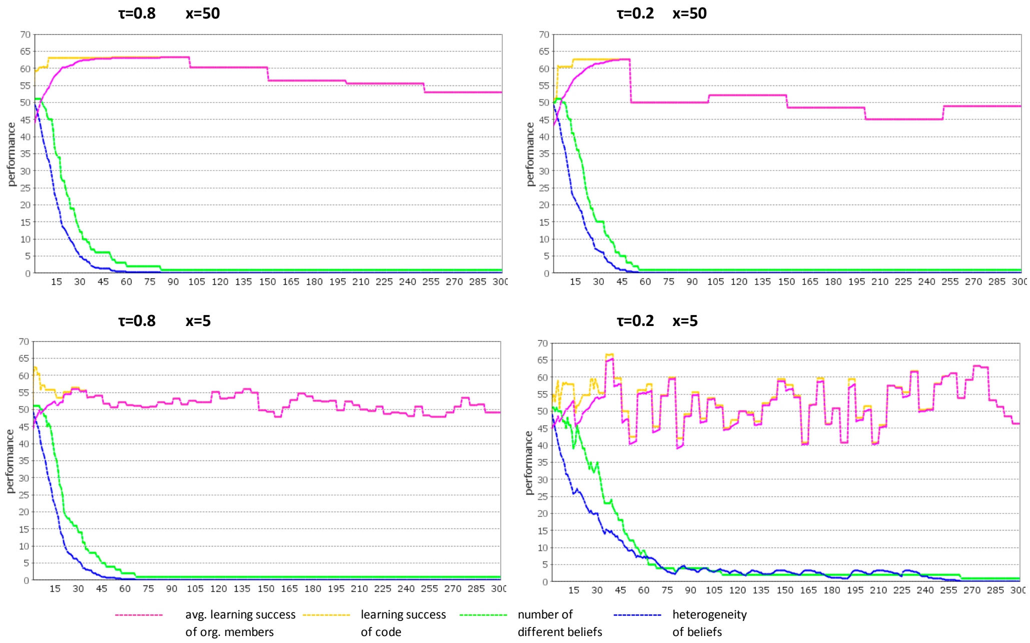


Figure 36: Mutual learning in the four specified scenarios of environmental turbulence (K=0; p_a=0.1; p_c=0.9), example runs

[249] See chapter 6.4.2.

Although the explanatory power of single model runs is limited,[250] they give a good impression of the general impact of the different change regimes. As expected, organizational knowledge degrades faster if the organization is confronted with changes of high scope. In settings with a high frequency of turbulence, change in the beginning of the learning process impacts when there is still much belief variety in the system. We can see from the graphs on the left side that the systems are able in the beginning to cope with environmental change, and their learning success increases despite of the impact of turbulence. Consequently, detrimental learning conditions shorten the phase in which the system is able to keep up sufficient learning activity to compensate for environmental change as can also be seen from the following figure.

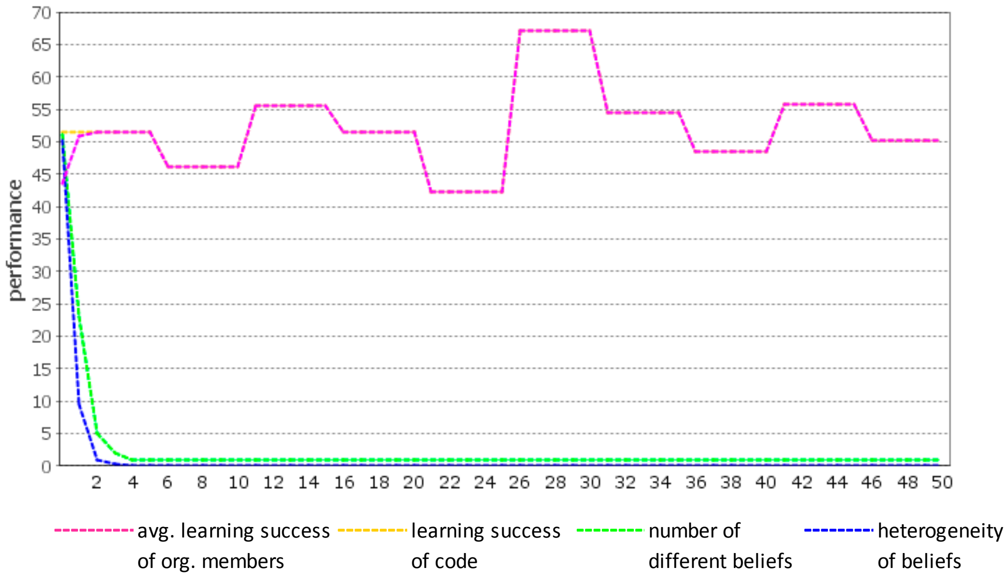


Figure 37: Example run with strong and frequent change in detrimental learning conditions (K=0; τ=0.2; x=5; p_a=0.9; p_c=0.1)

Before we start our inquiry into the learning dynamics in different regimes of environmental turbulence for which we will keep environmental complexity at a

250 For the configuration of the required number of model runs, see chapter 6.1.3.

moderate level, we ran a comparison showing organizational performance in different change settings for simple to highly complex environments (Table 11).[251]

Learning success	K0	K3	K10
Regular [τ=0.8; x=50]	0.965	0.912	0.856
Gradual [τ=0.8; x=5]	0.909	0.857	0.833
Disruptive [τ=0.2; x=50]	0.820	0.740	0.701
Hyper-turbulent [τ=0.2; x=5]	0.793	0.712	0.685

Table 11: Comparison of the average learning success of organizations in differently complex environments and different change settings (p_a=0.1; p_c=0.9), average values over 600 runs

In general, environmental turbulence leads to a decline of organizational performance when compared to stable environments. The usual decreasing performance of the organization with increasing environmental complexity is confirmed here for every regime of turbulence.

For the following experiments, we set environmental complexity to a moderate level ($K = 3$) and delve deeper into the effects of frequency and scope of turbulence on organizational learning. In accordance with chapter 6.3.3.1, first, we explore their effects in beneficial learning conditions, in which the code learns fast from the organizational members whereas these learn slowly from the code, before we compare the achieved results with the detrimental counterpart of the learning conditions.

The intelligence of organizations rests on the mechanism of mutual learning. Without exchange of good ideas improvement becomes inconceivable. Frequent and strong

[251] To report the learning success we used the normalized average learning success in the organization averaged over all 300 ticks. Each average learning success is based on 600 runs of the model. This allows us to compare between different complexities within the same regime of turbulence. For more information concerning this approach see Appendix H.

environmental change first of all disturbs this mechanism. Figure 38 shows a comparison of regimes of strong change impacting with different frequencies.

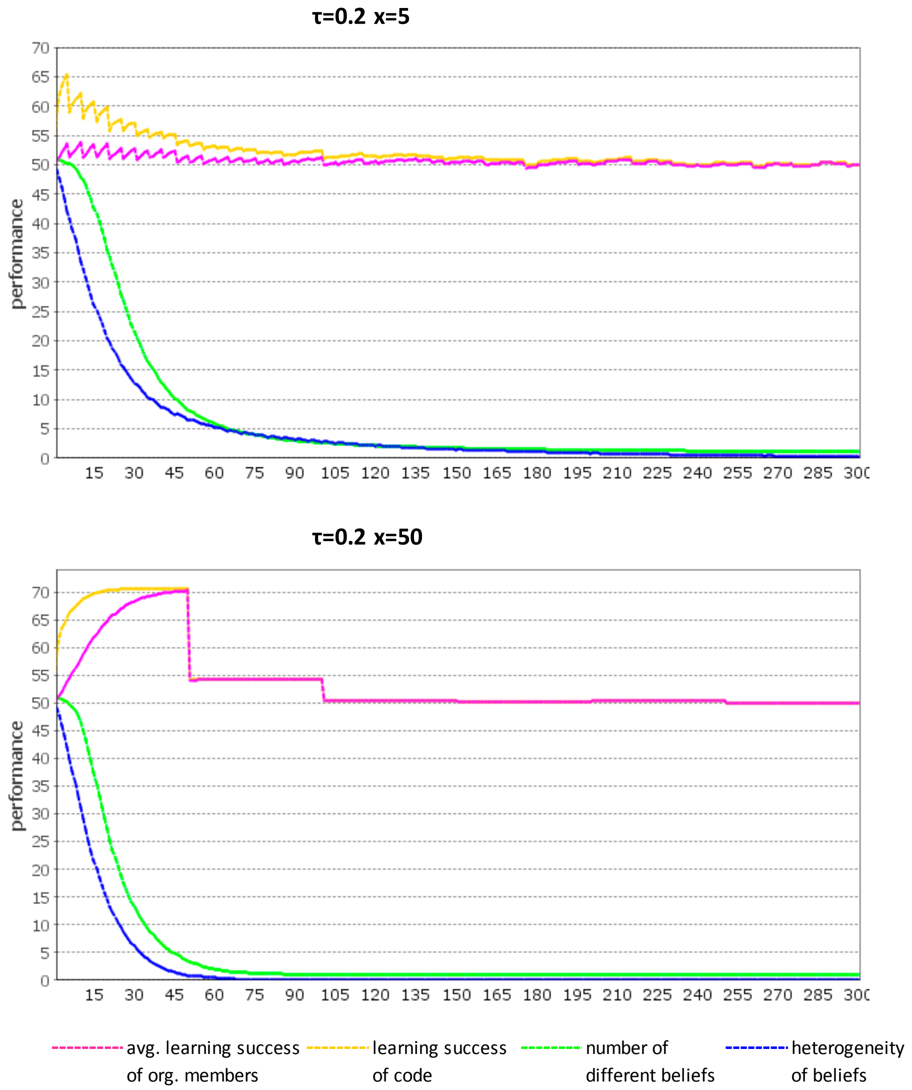


Figure 38: Mutual learning in complex environments with different frequencies of change (K=3; p_a=0.1; p_c=0.9)

With environmental change impacting every 50 time steps (second graph), in the beginning organizational knowledge has the chance to improve as if confronted with only a stable environment. Obviously, undisturbed mutual learning provides a strong ground for the improvement of organizational knowledge. We conclude that disturbing this process as a result of environmental change has a strong first order effect on organizational learning. But to explain the dynamics in the first graph, we have to go beyond the effect of mere knowledge degradation.

Figure 39 illustrates the learning dynamics for change settings which differ according to the specified scope of change. While the first graph here shows a regime with a mild impact of change, the second graph demonstrates the learning dynamics in a regime where change impacts strongly. Both graphs feature a similar change frequency.

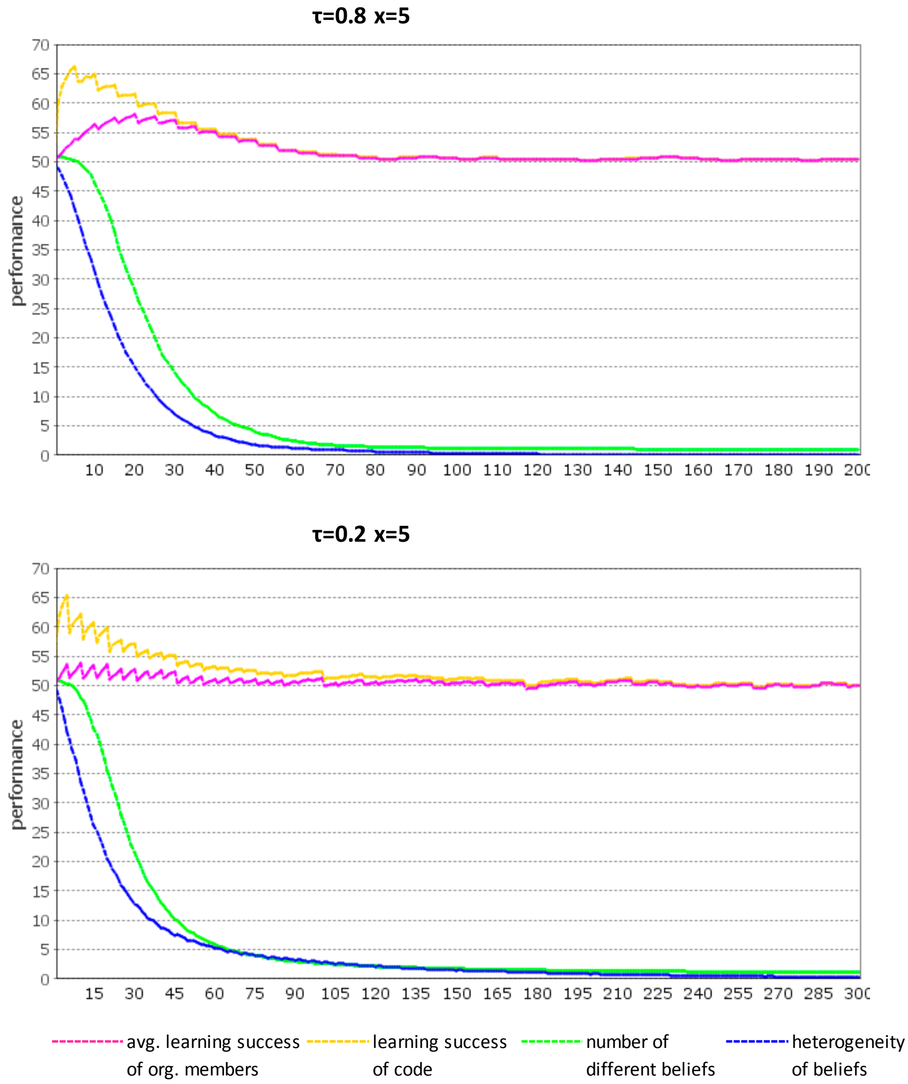


Figure 39: Beneficial learning conditions in complex environments with different scopes of change (K=3; p_a=0.1; p_c=0.9)

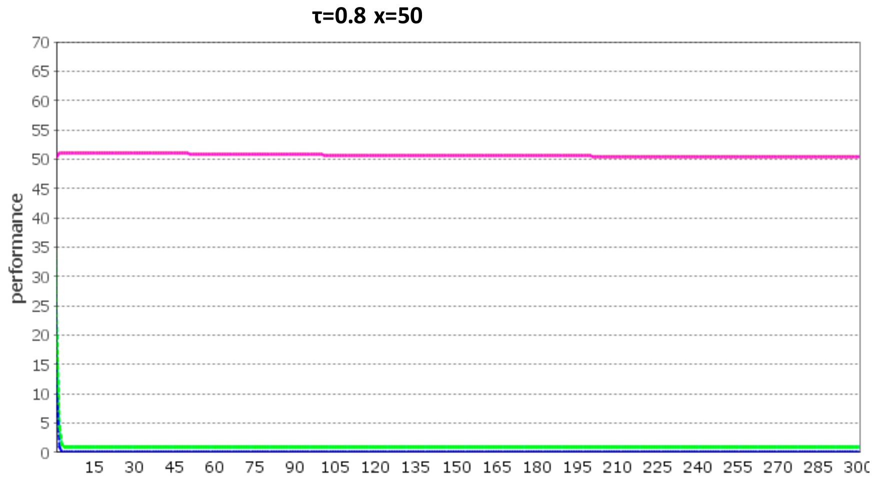
Clearly, two effects which influence organizational learning behavior can be identified from comparing the two differing change regimes. As expected, the average knowledge held by the organizational members (magenta curve) is degraded quickly if change impacts frequently. But in the process, the organizational code has more time available to learn from the organizational members. Intuitively, this should lead to a decline of code knowledge as the average knowledge of the individual members also declines. But this does not account for the whole effect shown in the above graphic. The code also profits from the prolonged diversity in the organization even if this diversity lowers the average learning success. Since the code selects the better performing agents, it is able to access good solutions which are created accidently based on the still existing belief variety. Here, we again encounter what March (1991) called the gains from diversity; there is a trade-off between individual and collective knowledge. The discrepancy between the belief-set held by the code and the belief-sets held by the organizational members caused by environmental turbulence, while not providing a gain to individual knowledge, provide a gain to collective knowledge.

The mechanism behind prolonging the belief convergence is a similar one as identified in regimes of increasing complexity. The mutual learning mechanism is distracted. After an environmental shift, a formerly inferior solution might prove superior (Kim & Rhee, 2009:24). The code then tries to follow the dynamic of the environment by turning to different solutions in the organization which again influences the socialization process.

If environmental change impacts frequently and affects the organizational learning process this has a strong negative effect on organizational knowledge, as already pointed out by Kim & Rhee (2009). Environmental change disturbs the exchange of good solutions moderated by the code. Likewise, in the case of especially strong and frequent environmental change, the change impacts while there is still belief variety left in the organization.[252] This endows the code with possibilities for improvement and also increases the time to convergence and as a consequence at least attenuates the negative effects of knowledge degradation.

[252] Please remember that in this chapter we deal with a model of merely mutual learning without any mechanism adding extra variation to the system.

Environmental turbulence is detrimental for organizations. It is only belief variety in the organization that provides the necessary capabilities for change (March, 1991:80). Even without any mechanism adding variation to the system, as turnover or individual exploration, it is therefore important when the environment changes. For detrimental learning conditions, as can be seen from Figure 40, the organization therefore experiences the mere first order effect of a decline in knowledge which is directly related to the scope of environmental change. The time frame for organizational learning at almost any rate here is shorter than the one of environmental turbulence. In this case, change impacts when the system is already locked in. In beneficial learning conditions, the system also approaches the lock-in state, as in this chapter it cannot generate variety out of itself, but there the impact of the different change regimes is moderated by the described second order effect.



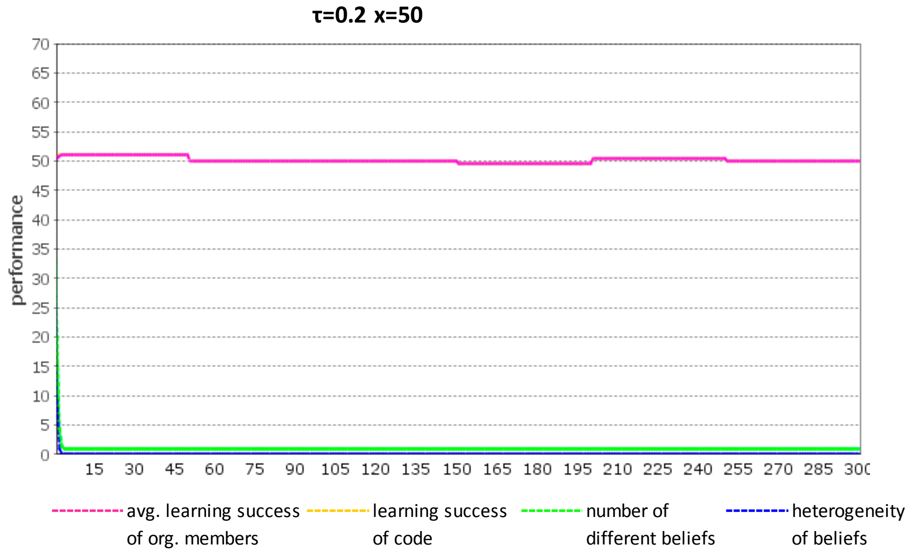


Figure 40: Detrimental learning conditions in complex environments with different scopes of change (K=3; p_a=0.9; p_c=0.1)

That the organization finally becomes path-dependent can only be counteracted by infusing variety into the system. March (1991), Kim & Rhee (2009), and Fang, Lee & Schilling (2010) explored the effects of personnel turnover occurring as random mutations of the belief-sets in mutual learning models. We consider individual exploration another worthwhile practice to integrate into a mutual learning model. As outlined before, it captures the experience-based learning activity of the organizational members and brings its own specific dynamics and restrictions. In the following chapter, we therefore examine if and how this mechanism is able to preserve system adaptability in turbulent environments.

6.4.3.2 Individual and Mutual Learning and the Impact of Environmental Turbulence

Previously we have dealt with the specified regimes of environmental turbulence in a model in which learning is moderated by an organizational code. Following an outline of increasing model intricacy, we continue our inquiry by integrating individual level learning into the mutual learning model. Learning of the organizational members based on the feedback they receive from the organizational environment incorporates new solutions into the organization and is therefore bound to increase its adaptability to changing environments.

Similar to the experiments conducted in the preceding chapter, we keep environmental complexity at a moderate level ($K = 3$). As the adaptability of the organization increases due to individual learning, we raise the number of time steps for each simulation to 1000 ticks, and even more if required. This ensures a sounder analysis as we can follow organizational behavior across a greater number of change cycles. Another important differentiation dealt with in this chapter refers to the explorative ability of the organizational members. We compare organizations featuring members with a high or low inclination for exploration by varying the pace of individual learning.

The following figure shows an example run of an organization which learns in a turbulent complex environment.

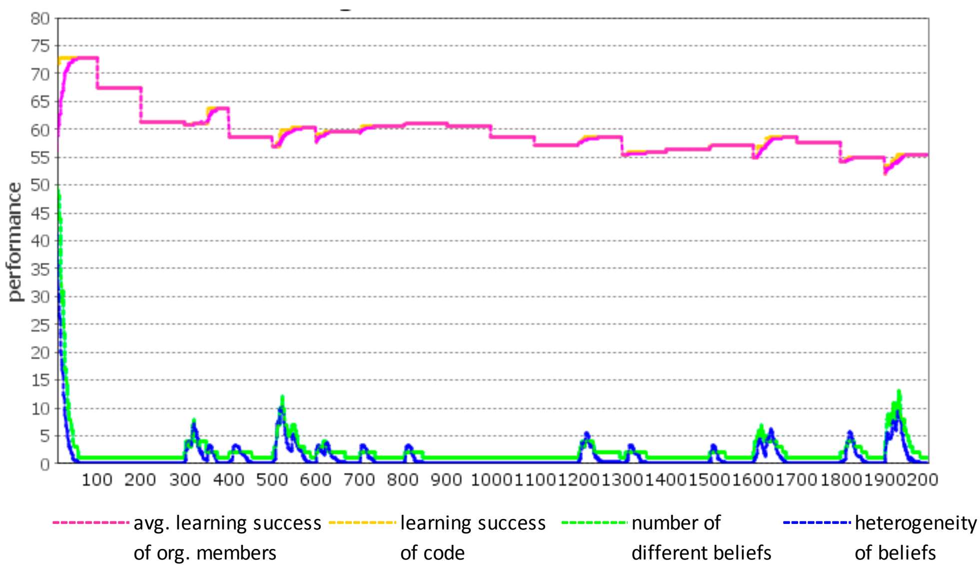


Figure 41: Example run with weak and infrequent change in beneficial learning conditions (K=3; τ=0.8; x=100; p_a=0.1; p_c=0.9)

In contrast to the preceding chapter, the organization is able to generate belief variety even after it has converged on a homogenous mind-set (green/blue curves). The change conditions here were set to isolate the effect of individual exploration. Environmental change impacts after the organization already converged. As the individuals in the organization do not solely refer to the organizational code for learning but also receive feedback for their activities from the environment, they at least infuse new solutions into the organization which, due to the myopic nature of the individual learning process, are bound to lie in close proximity to old solutions. Still, this process seems to allow the organization to at least adapt incrementally. Looking at the average learning success (magenta curve), we notice that it is a small scale adaptation. The generated heterogeneity is not sufficient to search the environment profoundly as in the beginning of the learning process. The organization does not return to its initial learning success but it also does not drop down to completely random scores.

We continue by exploring organizational behavior in different change settings for beneficial and detrimental learning conditions (Figure 42 and Figure 43). Based on these results, we start our examination of the effects of high and low exploration regimes (Figure 44). Similar to the graph above, although this shows merely a single run of the model, we expect change which impacts infrequently and weakly to lower the organizational learning success slowly. Showing the average model behavior over 600 model runs, this general pattern of environmental impact is visualized in Figure 42.

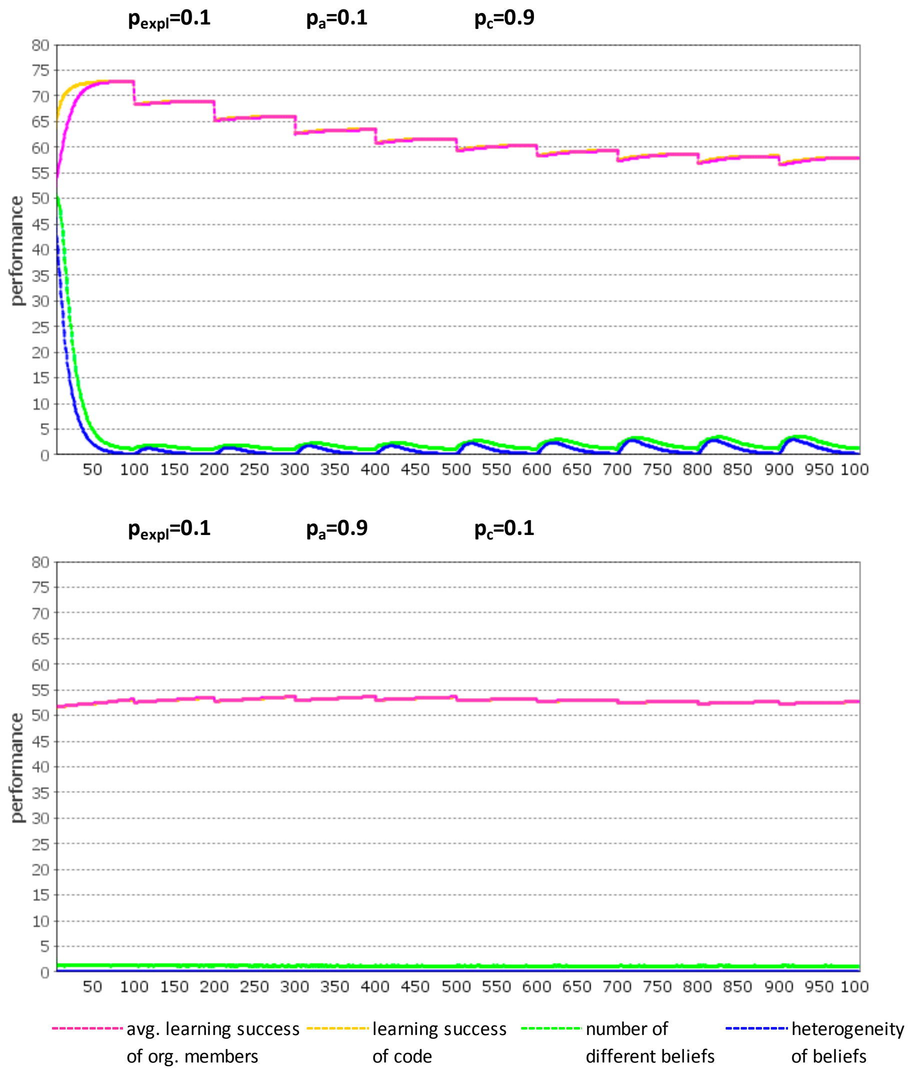


Figure 42: Comparison of beneficial and detrimental learning regimes in complex environments with weak, infrequent environmental change (K=3; τ=0.8; x=100)

From comparing the two different learning regimes presented in this figure, we can see that a fast socialization or learning from the code counteracts the beneficial effect of individual exploration. In a beneficial learning regime, the organization is able to profit from the incremental search of its members. The slowly decreasing learning success of the organization also implies that better solutions in the close proximity to the organizational belief-set emerge only eventually. The local search of the individuals starts from this homogeneous belief-set and is therefore not able to compensate for the initial loss of organizational performance.[253]

The organization in conditions of fast learning here stays more or less locked in to the code belief. The strong socialization leaves no time for the individual ideas to impact on the organizational level. The limited heterogeneity introduced by individual learning dies down before leaving any significant mark on the organizational learning success.

In contrast, when the organization is confronted with disruptive change, the decline in organizational performance at first is dramatic (Figure 43).

[253] See the increasing height of the heterogeneity cycles in the first graph of Figure 42.

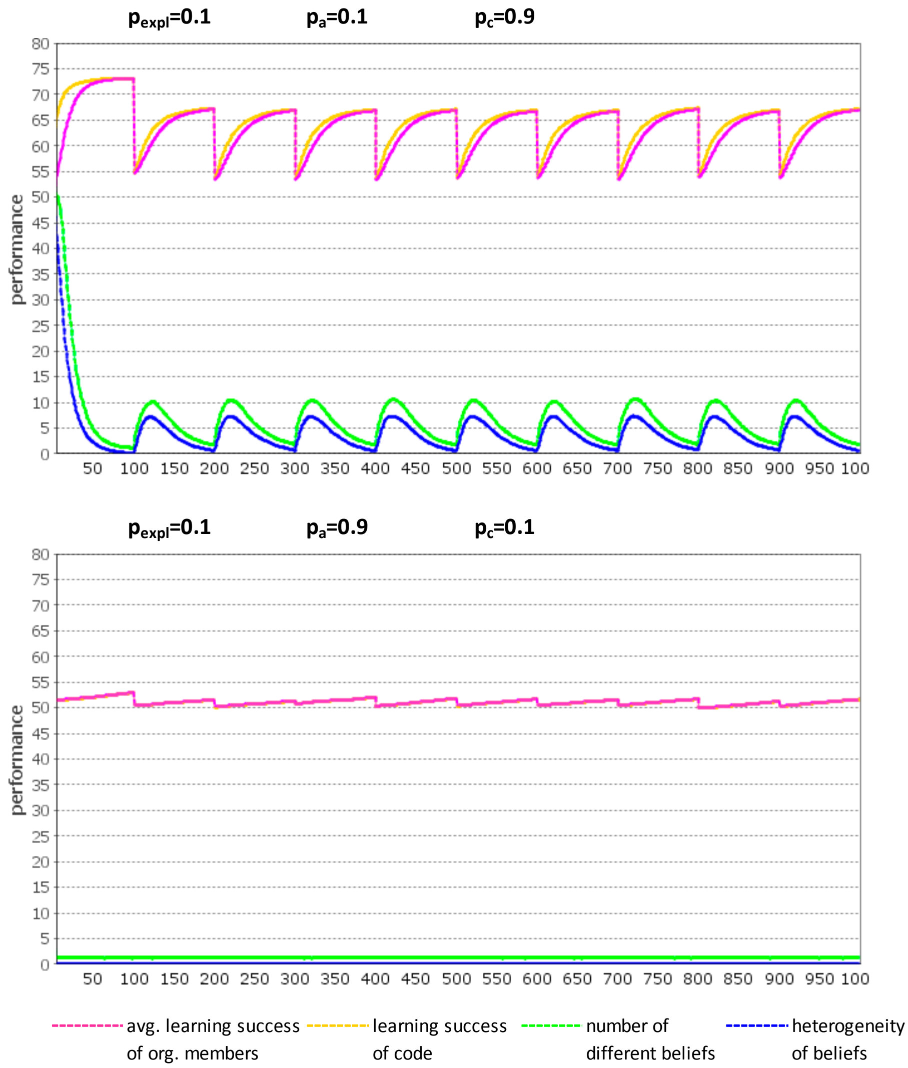


Figure 43: Comparison of beneficial and detrimental learning regimes in complex environments with large, infrequent environmental change (K=3; τ=0.2; x=100)

Environmental change of high scope leads to a redefinition of the value of many solutions in the organizational environment. While this strongly degrades the belief-set of the organization, at the same time it opens up new possibilities for individual learning. The organization experiences a rapid decline in its learning success but likewise individual learning incorporates a greater variety of beliefs right from the very first cycle of environmental change. Again, only in good learning conditions, individual learning contributes to organizational performance. In detrimental learning conditions, fast learning from the code almost renders individual exploration meaningless.

By comparing good learning conditions in both environmental regimes with low and high impact of turbulence (first graphs in Figure 42 and Figure 43), we realize that the improvement after each change due to individual exploration happens more slowly in regimes of low change. Individual search in high scope change regimes is able to generate a higher belief variety even if it starts from a homogenous location. The higher belief variety then induces the usual positive effects involved in the selection process conducted by the code. This gives rise to the conclusion that environments which are subject to changes of small impact might cause a lower average organizational performance than disruptive environments given that these provide the organization with enough time to distribute valuable solutions inside the organization. We come back to this later in this chapter, where we compare the average organizational performance of the organizational members and the code over the time steps of the simulation.

The above analysis shows that the interaction of mutual and individual learning guides organizational behavior in every cycle of environmental change. We find the mechanisms of mutual learning and individual learning differently pronounced in the different change regimes. In the following figure, we influence the interaction between the learning processes by equipping the organization with individuals who learn rapidly from their environment.

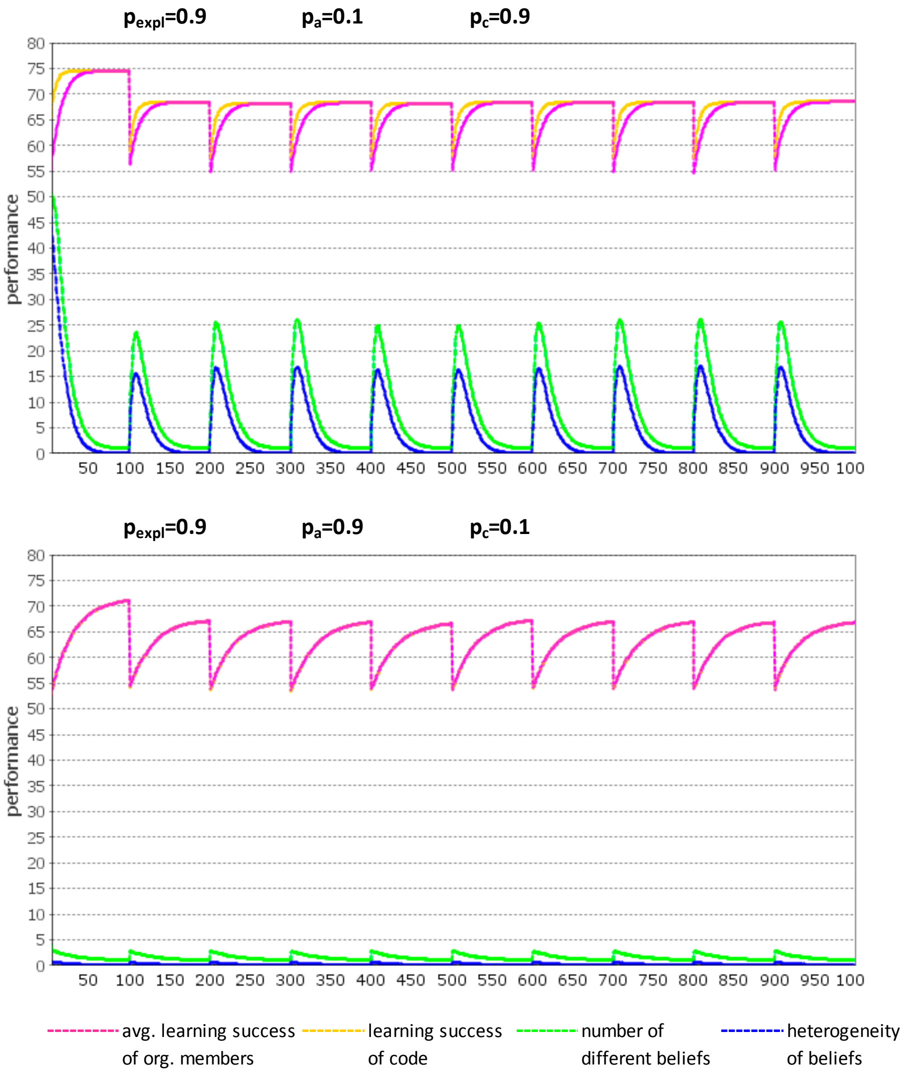


Figure 44: Comparison of beneficial and detrimental learning regimes with fast individual learning in complex environments with disruptive change regime (K=3; τ=0.2; x=100)

The two graphs in Figure 44 vary only in the conditions of the mutual learning process. While the first graph demonstrates organizational behavior with beneficial mutual learning conditions the second graph does so for detrimental conditions. Both graphs are based on similar environmental regimes and fast individual learning. We see that in good learning conditions the organization with high exploration generates even more variety and therefore succeeds in improving quickly. It does not approach its initial performance level but is able to increase its performance faster than in a low exploration setting. The second graph illustrates an astonishing increase of organizational performance after each environmental change for the detrimental learning conditions. Based on the low amounts of heterogeneity which are generated even in this high exploration regime, the organization improves performance significantly even if it does so more slowly than the organization in good learning conditions. Even this search in very confined spaces leads to considerable adaptability of the organization. We should notice, on the other hand, that to arrive at this level of adaptability, the organization in bad learning conditions has to keep up a very high level of individual search activities.

Between the two learning regimes we realize a difference concerning the behavior of the organizational code which also gives more background on the above described findings. In the first graph, code performance quickly rises above the average performance of the organizational members after each environmental cycle, in the second graph the two curves (yellow and magenta) are congruent. While in good learning conditions the individual exploration activities again activate the mutual learning mechanism of selecting and distributing good solutions in the organization, in detrimental learning conditions the intelligence of the organization rests mainly on the search behavior of the individuals which is confined to the restricted area of code expertise. As the organization in good learning conditions can fall back on a higher belief variety, its convergence on a new belief-set happens faster, showing in the first graph in a distinctive plateau region of organizational performance after each change. In detrimental learning conditions, the process is based on a low belief variety prolonging the incremental search process for the local optimum. Even if the organization improves eventually, the average performance over a number of time steps in the simulation hence, will thus be smaller in this learning regime.

The following tables give an overview of organizational performance in the different change regimes for various conditions of organizational learning.

avgScore	p_{expl}=0.1; p_a=0.1; p_c=0.9	p_{expl}=0.1; p_a=0.9; p_c=0.1	p_{expl}=0.9; p_a=0.1; p_c=0.9	p_{expl}=0.9; p_a=0.9; p_c=0.1
τ=0.8 x=100	0.621	0.529	0.627	0.614
τ=0.2 x=100	0.637	0.511	0.673	0.638

Table 12: Average performance of *individuals in organization* averaged over 1000 ticks comparing different environmental and learning settings

codeScore	p_{expl}=0.1; p_a=0.1; p_c=0.9	p_{expl}=0.1; p_a=0.9; p_c=0.1	p_{expl}=0.9; p_a=0.1; p_c=0.9	p_{expl}=0.9; p_a=0.9; p_c=0.1
τ=0.8 x=100	0.624	0.529	0.629	0.614
τ=0.2 x=100	0.649	0.511	0.683	0.638

Table 13: Average performance of *organizational code* averaged over 1000 ticks comparing different environmental and learning settings

Table 12 shows the average learning success of the organizational members; Table 13 exhibits the average learning success of the code (all results are average values of 1000 time steps and 600 runs). The tables further exemplify important effects mentioned in the above analyses. Again, we find a rather obvious first order effect in the knowledge degradation which is directly connected to the impact of environmental change. Three other effects can be identified which directly point us to the dynamics taking place in the model. First, we find that while detrimental learning conditions in every setting perform less well than their beneficial counterpart, the differences are far less pronounced in organizations which feature high individual exploration. Second, the differences between high and low exploration settings become more pronounced with increasing scope of environmental change, and they are more marked for detrimental learning conditions. Third, organizations in regimes with a high scope of change often outperform organizations in regimes with changes of low scope. The differences between the code score and the average individual performance give us further indication as to the dynamics taking place in the organization.

The described effects lead us to the following explanation. To compensate for bad learning conditions, at least partly, the organization requires very high levels of individual exploration. Because in these learning conditions the local search mechanism of the individuals dominates, the organization needs more time to converge on a local optimum, an effect similar to the one found in chapter 6.3.3.2.[254] The low belief heterogeneity generated even with high exploration constitutes a more confined search of the landscape and, consequently, on average produces less good solutions. Moreover, the low belief heterogeneity and the dominance of the local search mechanism account for a much slower increase in performance which additionally lowers the average learning success of the organization across cycles.

In beneficial learning conditions, the organization reaches relatively high levels of belief heterogeneity in every change cycle even with low levels of individual exploration. Knowledge is then incorporated into the code based on a high belief variety leading to a broader exploration of the problem landscape and a quicker process of convergence.

The dynamics for each change cycle which result from the interaction of the two mechanisms in the model are similar to the ones identified in chapter 6.3.3.2. The average organizational performance across cycles is crucial if we move from a stable environment with individual exploration as explored in chapter 6.3.3.2 to a turbulent environment where we have to consider the time to convergence on a homogeneous belief-set an important criterion for organizational performance. To conclude our exploration in turbulent environments we therefore proceed by inquiring into environments which feature more frequent changes.

Figure 45 compares organizational learning in frequently changing environments which differs in the conditions of learning. Independent from the learning regimes, frequent change interrupts the process of knowledge convergence in the organization.

[254] Please note that we do not compare across regimes of different complexity but keep complexity stable.

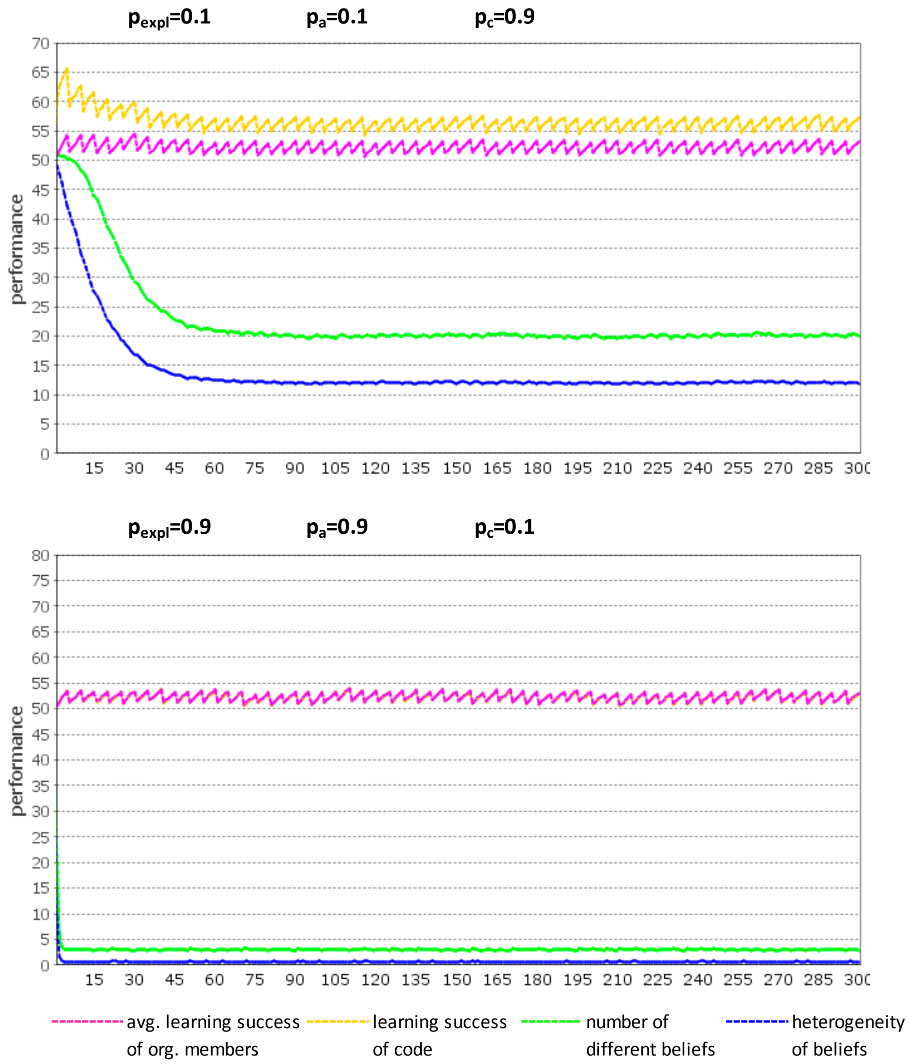


Figure 45: Comparison of beneficial and detrimental learning regimes in complex environments with frequent change (K=3; τ=0.2; x=5)

The graphs and also the following table show that high belief heterogeneity in the organization cannot necessarily be equated with good learning performance. Despite a high level of belief heterogeneity which is preserved in hyper-turbulence due to the exploration of individuals, the organizational performance suffers.

avgScore	p_{expl}=0.1; p_a=0.1; p_c=0.9	p_{expl}=0.9; p_a=0.1; p_c=0.9
τ=0.2 x=5	0.522	0.555
τ=0.2 x=50	0.610	0.658

Table 14: Average learning success of organizational members over time (300 ticks) for different environmental and learning regimes

In beneficial learning conditions, the code is able to profit from the resulting high belief heterogeneity (see yellow curve in first graph of Figure 45). Whereas the average learning success of the individuals in the organization stays low (see Table 14), the code score surpasses the average learning success. Still, as the mutual learning process is interrupted by the preceding environmental change, the organizational learning cycle is not completed.

Organizations with detrimental learning conditions which decrease belief heterogeneity quickly cannot cope with frequent change environments. In frequent change environments, the dominant local search mechanism of these organizations does not have the required time to impact on the organizational level.

In chapter 6.3.3.2, we claimed that the variety added to the organization by competence-enhancing learning of the organizational members is different from the one added by personnel turnover. In stable environments, its main contribution on an organizational level lies in evaluating the potential of solutions in the organization. Declining variety in the organization therefore reduces the effectiveness of individual exploration. The organizational learning result as well as the speed of convergence depend on the dominance of the different learning mechanisms. As individual learning does not produce solutions which are entirely detached from the organizational knowledge set, even extensive exploration does not harm the organization.

In turbulent settings, similar to personnel turnover, individual exploration in many learning regimes assures at least a certain adaptability of the organization to its environment. But, in contrast to turnover, individual exploration is triggered by the change in the organizational environment. In turbulent settings, we find a similar behavior of the organization as described for stable environments if the cycle for environmental change is longer than the one for organizational learning. If environmental change interferes with the organizational learning cycle, the learning result is much harmed. Here, organizations in detrimental learning conditions in which individuals explore based on a low belief variety show almost no adaptability to the changing context. Organizations with beneficial learning conditions in which the local search mechanism starts from a high belief variety despite a limited time frame still profit from the high belief heterogeneity which is sustained by exploration.

Chapters 6.3.3 and 6.4.3 gave a detailed description of the results of our model of path dependent learning in complex and turbulent environments. In our discussion in chapter 7, we will aggregate the most important findings and point out their theoretical implications. Before we proceed to this step we refer to the model's robustness and discuss its validity.

6.5 Robustness of the Results

The robustness of a model refers to its sensitivity to changes in the parameter values and the assumptions made in the model (Gilbert & Troitzsch, 2005:24; Davis Eisenhardt, & Bingham, 2007:492). The results which are presented after conducting computational research almost always reflect only a small range of the produced outcomes. During the research process, simulation behavior usually is explored extensively (Siggelkow & Rivkin, 2005:116). To fulfill the requirement of a robustness check, this extensive exploration of the model has to cover all relevant parameters. Of course, not all parameters in a simulation are relevant candidates for an analysis of robustness. Most of the parameters given in the overview in Appendix A concern the internal working of the simulation and are not externally set. Their plausibility was tested in the debugging process of the model. Such an overview of all simulation parameters which is based on the software code nevertheless increases the transparency of the simulation and provides a good starting point to deal with the robustness of a model. Besides the parameters which reflect the independent variables in a simulation, nuisance factors here are of special importance. To prove the robustness of our model results, in the following section, we refer to several steps made during the preparation of the experimental phase.[255]

Nuisance factors in a simulation can be controllable or uncontrollable. Controllable nuisance factors, meaning parameters that can be externally set in a simulation, are what we referred to as control variables.[256] In the simulation, we have six different control variables, the number of time steps ($ticks$), the number of model repetitions ($runs$), the number of agents (pop), the number of better performers that the code accesses for learning ($numBetterPerf$), the number of environmental dimensions (N), and the parameter specifying if during environmental change the dependencies in the NK landscape are kept ($keepDependenciesOnChange$). All of these parameters and their influence on model behavior were subject to intense exploration conducted in different steps. In the following section we briefly refer to its outcome for all control variables relevant for the model with and without environmental turbulence.

As usual in the specification of problem landscapes, we set N and pop to achieve a sufficient difficulty of the problem that the organization has to solve. The effects of other configurations of N and other population sizes which were explored with an increase or decline in dimensionality and number of agents searching for solutions showed the expected effects.[257]

The number of time steps defined for the experiments were based on an exploration of the convergence behavior of the model for a stable environment, as can be seen in Appendix E. Investigating the fluctuating behavior of the model with the logic for learning by the code as employed by March (1991) also made it necessary to run the model with extreme amounts of ticks ($> 10.000\, ticks$). For the first set of experiments, the number of ticks ensures that the model converges in every run so that the performance reported reflects the organizational performance with a homogenous mindset.

In chapter 6.3.3.1, we dealt in detail with the effect of the parameter setting the size of the elite that the code identifies for learning. Appendix G (Figure 49, Figure 50) shows

[255] See chapter 6.1.

[256] For a description of the control variables in our model see chapter 5.4.3.

[257] See chapter 6.1.2, setting of N and pop in Figure 21.

that the model employing the logic of March (1991) and different sizes of the elite group was simulated extensively. We compared a broad range of different learning regimes and the resulting dynamics for different logics. We also investigated logics for learning by the code which are not reported here but we found in similar models. The basic dynamic of the original model in a simple environment and the effects of fast and slow learning are not changed by an elite of sensible size. Of course, a very large elite ($numBetterPerf = pop - 1$) is bound to stop learning altogether, as in this case the selection process of good solutions in the organization is terminated. Still, the size of the elite exerts a strong influence on the intensification of the learning process. Although a focus on the best performer in the organization will limit belief diversity it also increases performance in a stable environment. Based on these findings, we specified a medium sized elite ($numBetterPerf = 5$).

The parameter which specifies if the interaction effects between the environmental dimensions are kept when the environment changes ($keepDependenciesOnChange$) was defined when configuring the model for experimentation. Switching it on caused a further decline in solution quality after an environmental change, without impacting the general dynamics of the system after a change.

Another parameter which can be and in our case is treated as a control variable is the number of runs. Exploring the effects of different amounts of runs in different model settings has the benefit of being able to specify which amount of runs is needed to ensure that the variation observed between different settings in the model is not due to noise factors in the simulation (Lorscheid, Heine, & Meyer, 2007:10). With our estimation of variance we therefore also accounted for the uncontrollable variation in our model. We described the outcome of our estimation of error variance in chapter 6.1.3 and in further detail in Appendix D. Here, simulation behavior is tested and compared for many design points specifying different combinations of the independent variables and different amounts of runs. An estimation of error variance thus provides the researcher with a broad assessment of the simulation behavior in different conditions. Our preliminary design points reflect the complete parameter ranges available for the different learning speeds. For every design point we repeatedly ran the simulation with increasing number of runs and for the dependent variables calculated the coefficient of variance (Lorscheid, Heine, & Meyer, 2011:12-13). Therefore, the estimation of variance can be considered a robustness study with the additional beneficial effect of also specifying the number of runs required to achieve significant results.

In the subsequent chapter our main focus is on aggregating the simulation results and discussing how they contribute to research on path dependence and organizations.

7 PATH-DEPENDENT ORGANIZATIONAL LEARNING AND THE ENVIRONMENTAL CONTEXT: DISCUSSION

This dissertation set out to answer the question how the environmental context influences the path-dependent characteristics of organizational learning. To solve this problem, we followed a step-by-step approach. Important steps in this process centered around aggregating the complex and abundant literature on organizational learning and building a theoretical model which involved the dynamics identified in organizational learning and afterwards transferring this theoretical approach into a computational model. Every solution we present here and which is based on the experimental chapter is first of all a solution to the model of our problem (Michalewicz & Fogel, 2004:16). Consequently, the experiments conducted with the model show the effects of environmental complexity and turbulence on the modeled dynamics. In real, non-artificial organizations, the dynamics are doubtless confused by other conditions and effects. As outlined before, we consider our model not as a predictor of organizational behavior but as a means for testing and appending theory (Davis, Eisenhardt, & Bingham, 2007). In the last chapter of this dissertation, we draw conclusions on the results produced by the model. As with any approach which is purely theory-based, our results can therefore only stretch as far as the assumptions in our model hold (Lazer & Friedman, 2007:688) and are applicable only for the limited considered dynamics.

Our first step in this concluding chapter concerns the validity of the model and its findings. Subsequently, we continue by discussing the implications of our results for path dependence theory and research on organizations. This central part summarizes the simulation results and connects them to existing research. The explanations of the simulation results again are guided by the two central dynamics identified in path-dependent organizational learning. Based on this, we point to the limitations of the model and give an outlook on future research. We finish this dissertation by giving a brief overall summary.

7.1 Validity of the Model and its Findings

Proving the validity of computational models is challenging since there exists no standard approach which is applicable in all situations. Burton & Obel (1995:115) claim that the validity of a model is closely connected to its purpose; it is thus a result of matching the research question, the computational model and the experimental design. Validity is therefore something which is achieved in various steps in the computational research process and which also develops in close connection to the purpose of the research. Carley (2009:54-55) suggests several principles in the research process which contribute to the validity of a model.[258] In the following, we review these principles and relate them to our research:

Principle 1: Understand the trade-offs in the system you are modeling.

The first principle Carley (2009:54) mentions refers to the ability of the researcher to identify the core relationships and tensions in the modeled system. To model a system credibly, the researcher is therefore obliged to carefully consider which entities, processes and resulting interactions must be accounted for. In our theoretical chapter,[259] we put a special emphasize on understanding and in consequence detailing the workings of learning effects in organizations. Our theoretical framework describes the elements and processes at work at different levels in the organization and accounts for their interaction. In chapter 4, we further increased our understanding of the trade-offs involved in organizational learning by discussing the two learning dynamics in our framework with respect to existing learning models. From this discussion we derived an assessment as to the contradicting effects of the processes at different levels in the organization.

Principle 2: Clearly define the purpose of the simulation.

It is essential for good simulation research to be precise about its purpose. Burton & Obel (1995:63) claim that *"[t]he purpose of the computational model provides the anchor."* As the purpose of a simulation drives its level of veridicality, by defining the purpose, the researcher predetermines many aspects concerning the design and

[258] Maxwell & Carley (2009:213-224) in their article about effective representation of multi-agent systems detail these principles.

[259] See chapter 2.2.

validation of a model. In our methodological chapter,[260] we explained several purposes for simulations on a continuum between aiming at prediction or generating hypotheses. We outlined our simulation as being in between the two extremes and considered it to aim at testing path dependence theory and giving theoretical implications as to the integration of the environmental context. We further narrowed down the implications which can be produced by our model to the area of learning effects in organizations. The purpose of our model is thus to show how environmental variables impact on learning effects.

Principle 3: Use good modeling practices.

From the purpose of the simulation in the preceding paragraph we go one step further to the design of the model. Besides pointing out the importance of choosing the appropriate organization, methods, and tools for the programming tasks, which is relevant for every software project, Maxwell & Carley (2009:213-214) highlight that, for simulations in the social realm, dealing with the uncertainty in the model is of special importance for the credibility of the research. Due to the complexity of the models, two levels of uncertainty become relevant, uncertainty concerning the state of a specific variable and uncertainty with respect to the structure of the model itself. As recommended by Maxwell & Carley (2009:214), we dealt with the uncertainties by describing the low-level behaviors in our model as detailed as possible and systematically inquired into their outcomes on the simulation result. We captured these additional variables which detail the process of learning by the code and the manner in which change is introduced into the environment in our control variables.[261]

Principle 4: Clearly specify all independent, dependent and control variables as well as all agent behavior.[262]

Principle 4 refers to disclosing the model's internal functioning and imposes a requirement for completeness as it emphasizes the necessity to account for all features of the model. The principle consequently aims at increasing the transparency of simulation research, which again contributes to its validity. Simulation models generally encompass a large variety of variables which influence model behavior. In

[260] See chapter 3.2.3.

[261] See chapter 5.4.3 and Appendix A and G.

[262] Carley (2008) refers to variables and agent behavior in two separate principles.

chapter 5.4, we gave a comprehensive overview of the variables in the model which classified all variables as dependent, independent, or control variables. As recommended by Lorscheid, Heine, & Meyer (2010:12-13), this classification takes the program code as a reference point and ensures that all variables which impact model behavior are included. Besides enhancing the transparency of the research, the classification of variables prevents the effects of non-focal variables from being overlooked. For every variable, including the control variables, we gave a precise mostly formal specification.[263] Similarly, we accounted for every element and process featured in the model formally or in terms of describing its behavioral rules (Harrison et al., 2007:1233).[264]

Principle 5: Conduct verification and validation exercises as warranted by the purpose of the model.

Verification closely relates to the concept of internal validity or in other words *"Did I build the model right"* (Maxwell & Carley, 2009:221)? We ensured that our simulation program worked as intended by using several procedures. To ensure its functioning on the micro level we employed a method-by-method debugging approach in which the output of every method in the program code was checked. The functioning on the system level was examined by running extreme situations and test cases in which the model behavior could be easily assessed (Gilbert & Troitzsch, 2005:22). Graphical output of the simulation data simplified the detection of errors.

Validation in turn refers to how well the simulation represents the target.[265] It relates to the concept of external validity and is concerned with the question *"Did I build the right model"* (Maxwell & Carley, 2009:221)? Burton & Obel (1995:63) point out that validity must be specified in terms of the purpose of a model. It is the purpose of the model which defines its level of realism[266] and consequently impacts all subsequent steps in the modeling process. Validation is thus strongly impacted by the level of abstractness of the model. Carley (2009:56-57) in this respect argues that for social

[263] This also points out a particular strength of simulation research. Due to the clear-cut specification and measurement of constructs, simulation research is not subject to any errors in measurement, providing it with high construct validity (Davis, Eisenhardt, & Bingham, 2007:490).

[264] See chapter 5.2 on the elements and 5.3 on the processes in the model.

[265] See chapter 5.7.2 on the model verification.

[266] Burton & Obel (1995:61) here suggest that realism is important but only within the context of the purpose as otherwise models become so complex that cause and effect relations are blurred.

science simulation, validation procedures of engineering models are inappropriate and calls for a new science of validation for behavioral models. She also acknowledges that for models whose variables are not unequivocally measurable, as it is the case in our model, validation in the usual sense is not feasible. Harrison et al. (2007) further support this position with the following argumentation:

> *"Purely theoretical simulation work should not be avoided simply because grounding is not available; it is still a legitimate scientific endeavor with the potential to make important contributions to management theory"* Harrison et al. (2007:1242)

To partially counteract the missing empirical validation, we provided validation at least in the sense that our model is able to replicate results of models which are acknowledged in the research community.[267]

Principle 6: Assess model results by running well structured experiments.

With respect to the simulation experiments, the validity of a model is enhanced by employing a highly structured design of experiments and by providing reliable results. The reliability of results depends on the number of iterations of the model and on the robustness of the simulation to changes in its parameters. In an estimation of error variance, we calculated the number of runs needed to achieve statistically meaningful results.[268] This procedure is based on an extensive inquiry into simulation behavior at different combinations of parameters. As the procedure aims at covering the complete parameter range, it gave us a valid picture of the robustness of the simulation. In our simulation experiments we employed a building block approach, moving from simple settings to more complicated ones in order to make results traceable. For every setting, we inquired into defined combinations of the learning rates for all specified configurations of environmental complexity and turbulence to ensure a fine-grained analysis of results.

Principle 7: Clearly present results and discuss limitations.

The last principle mentioned by Carley (2009:55) pertains to the presentation and discussion of the simulation results. A comprehensible presentation of results and a conclusive discussion of the limitations of the research similarly contribute to the

[267] See chapter 6.2.

[268] See chapter 6.1.3 and Appendix D.

validity of simulations. The step wise increase in model intricacy in our experimental chapter[269] aimed at facilitating the interpretation and understanding of achieved simulation results. Results were also made accessible by using graphical aggregation of the simulation data displayed as average values over the required number of model runs. For every experiment, we used the same type of figures to allow for fast interpretation and easy comparability. The large number of experiments nevertheless led to large amount of results which in the end impedes an easy conclusion. In the subsequent chapter, we therefore aggregate our simulation results by relating them to the central dynamics in our model and point out their theoretical implications. Following this, we also discuss the limitations of this research and point out future directions.

7.2 Implications for Path Dependence Theory and Research on Organizations

Our study is motivated by the fact that research on path dependence so far has mostly neglected to inquire into the influence of the context on path-dependent developments. Studies which have considered path-dependent processes to be embedded in specific environments have pointed out the relevance of the context for the unfolding of path dependence (Pierson, 2000; North, 1990) but fall short of explaining the particular impact of contextual conditions (Koch, Eisend, & Petermann, 2009:68). For organizational path dependence the context should be especially salient as it deals with persistence at the micro level of firm resources, capabilities, and strategies (Vergne & Durand, 2010:740). These lock-ins can be the result of four different self-reinforcing mechanisms from which we considered learning effects to be at the heart of our study as organizations adapt to their environments in processes of learning.

In our theoretical framework, we claimed that learning effects are characterized by interacting dynamics at the organizational and individual level. Furthermore, we outlined that each learning dynamic embodies its own specific path-dependent characteristic. Path dependence in learning can thus have two drivers, a mechanism of social adaptation or the competence-enhancing nature of experiential learning. We

[269] See chapter 6.

saw that much of the difficult nature of the twin concepts, exploitation and exploration, can be attributed to the fact that learning differs in its effects with regard to its level of impact. Each dynamic contributes to exploitation at its respective level but has explorative effects on the other one. Our learning model integrates both dynamics by combining two well-known modeling frameworks: the mutual learning and the NK landscape approach. In the simulation experiments, we inquired into the effects of environmental complexity and turbulence on the dynamics in our integrated model. In the following section, we translate our simulation results into a theoretical discussion by dealing with every environmental characteristic in turn.

7.2.1 Environmental Complexity

The following discussion reflects on the question: How does environmental complexity influence path-dependent organizational learning?

In the first part of this chapter let us review our speculations based on the model dynamics in chapter 4.3. We here referred to the argument of Sydow, Schreyögg, & Koch (2009:700) that environmental complexity cannot be considered a necessary or even sufficient condition for organizational path dependence. We criticized this proposition by pointing to the dynamic in individual learning. As *"[c]omplexity and bounded rationality are (…) two sides of the same coin"* (Koch, Eisend, & Petermann, 2009:71) it is thus likely that without these aspects learning will lead to efficient results. Consequently, in trivial circumstances even highly restricted incremental learning of the individual is able to avoid path dependence. We therefore pointed out that, with regard to learning effects, environmental complexity must be considered a necessary but, most probably, not a sufficient condition for path dependence to occur. Our experiments confirmed this simple assumption. The integrated model showed that in simple environments the organization converges on one belief-set which is always the global optimum. Since we considered efficiency a defining property of a lock-in, for learning effects to lead to path dependence complexity can be argued to be a necessary condition. On the other hand, complexity turned out not to be a sufficient condition for path dependence. Complex environments do not always create path-dependent learning results; organizations are able to learn the efficient solution even in complex circumstances.

Individual learning in our simulation bears similarity to the findings of Koch, Eisend, & Petermann (2009) in their study on individual decision-making. Here, complexity acts upon decision quality which in turn impacts on path dependence. Decision quality here was identified as a mediator which explains the effect of complexity on path dependence. Consequently, in simple circumstances where the optimum solution can be acquired easily and hence decision quality is high, the individual will not become path-dependent in the sense of ending up with an inefficient solution. In simple environments, learning becomes too trivial for path dependence to occur.

This supports our claim that we must not leave the individual learning process out of the picture as it is essential for the intelligence of organizations. As already pointed out by Burgelman (2002:351-352) and Hedberg, Nystrom, & Starbuck (1976:49) the organizational members act as sensors to the organizational environment and introduce new solutions into the organization. If an organization becomes path-dependent in simple environments it must be due to other mechanisms in addition to the dynamics of mutual and individual learning which interfere with the individual solutions becoming incorporated on the organizational level. Burgelman (2002:350-355) referred to this danger as the internal selection environment not mapping the external selection environment. Path dependence resulting from mere learning effects depends on environmental complexity.

Our results consequently point in a similar direction as North’s (1990) study on the path of institutional change. North (1990:95) here criticizes Arthur (1989) and David (1989) for neglecting the contextual effects of imperfect markets and claims that without the conditions created by imperfect markets the long run results of markets despite the presence of increasing returns will still be efficient ones. For North (1990), imperfect markets yield complex conditions which make deciphering the environments by the actors a difficult task. Similar to the dynamics in our model, it is only in complex conditions that the actors are unable to update and correct their mental constructs which shape the choices they make and yield path dependence.

After discussing complexity as a necessary condition for path dependence by relating the results of our model to existing literature, we proceed with a discussion of how differing degrees of complexity impact path dependence. With this, we particularly aim at detailing the precise impact of contextual complexity on path dependence.

In chapter 4.3, we already pointed out the interplay between the dynamics of mutual learning and individual learning. In the following section, we explain the impact of environmental complexity with respect to the two differing mechanisms of learning and their different effects on the individual and organizational level. Ackermann (2003:242-245) explained in which sense learning processes can be considered path dependent. He refers to the individual learning trajectory and the constant exchange of knowledge and ideas in social contexts which leads to converging mindsets. We complement his view with another important aspect of the individual and social learning processes which is also of crucial importance for the way the organization deals with complexity. While solely individual learning as argued by Ackermann (2003) leads to many divergent belief-sets, integrating both learning processes not only homogenizes knowledge in the organization but it also makes the organization astonishingly intelligent. Ackermann (2003) does not consider the interaction between both learning mechanisms and as a result neglects their explorative qualities. Learning at the individual level results in lock-ins due to myopic search while organizational level learning causes lock-ins due to excessive homogeneity. We found that both path-dependent dynamics in interaction do not increase the likelihood of path dependence but make path dependence less likely as paths on the individual level are able to dislodge paths on the organizational level and vice versa. This interaction does not entirely prevent inefficient results but increases the ability of the organization to deal with complexity.

Pierson (2000) argues that the murkiness of environments raises the probability for path-dependent outcomes. We certainly found a similar effect with respect to increasing complexity in our model but likewise were surprised by the ability of the organization to tackle surprisingly complex environments. In measuring the way complexity acts upon path dependence, we found the following implications by varying the speed of the learning processes. We examined organizational behavior in beneficial and detrimental learning regimes, much in the manner of March's (1991) slow and fast learning.

Table 15 summarizes and compares what emerged from our simulation experiments on complexity:

Env. complexity / Results	Simple environment	Moderately complex environment	Highly complex environment	
Belief convergence	fast *(high belief variety during learning process resulting in fast identification of optimum solution)*	medium *(belief variety preserved longer, lock-in of organization delayed)*	slow *(belief variety preserved even longer, lock-in further delayed)*	Beneficial learning regime
Learning result	efficient	slightly inefficient	moderately inefficient	
Belief convergence	very slow *(steep decline of initial belief variety, optimum approached very slowly from few similar belief sets)*	slow *(steep decline of initial belief variety followed by slow convergence of remaining belief variety and lock-in)*	slow to medium *(steep decline of initial belief variety followed by slow to medium belief convergence and lock-in)*	Detrimental learning regime
Learning result	efficient	moderately inefficient	highly ineffcient	

Table 15: Overview of simulation results in differently complex environments

The following main findings are crucial for the relationship between path dependence and complexity:

1.) In simple environments, the organization arrives at the global optimum independent of the learning regime.

2.) In simple environments, the organization in a beneficial learning regime shows fast convergence on a homogeneous mindset, while in a detrimental learning regime, convergence is slow.

3.) With increasing complexity, in beneficial learning regimes the time to belief convergence increases while in detrimental learning conditions it declines.

The first finding emphasizes the necessity of complexity for path-dependent outcomes. Bearing close resemblance to the results of Lazer & Friedman (2007:682), in trivial circumstances performance differences between the learning regimes vanish, making complexity a necessary condition to distinguish between the learning regimes.

The second finding shows the most obvious effect of individual learning. In agreement with Koch, Eisend, & Petermann (2009:79) who found that neglecting future developments for the sake of present information is an important part of path-dependent developments, individual learning contributes to evaluating the potential of present solutions in the organization. Thus, organizations which command a high diversity of beliefs are able to profit more from individual learning. The organization in beneficial learning conditions is therefore able to identify the optimum more quickly than the organization in detrimental conditions.

The result can also be explained with respect to the two mechanisms of learning in the model (see Table 16).

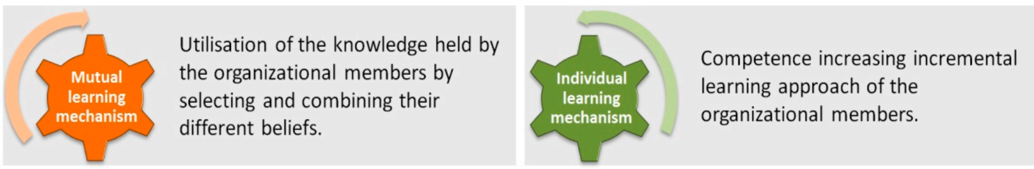


Table 16: Mechanisms of mutual and individual learning

Detrimental and beneficial learning regimes differ with regard to how pronounced the mechanisms of learning are in each setting. While in detrimental learning conditions belief variety declines quickly and the individual learning mechanism prevails in the organization on its long climb to the global optimum, in beneficial learning conditions, the mutual learning mechanism is strong. Here, the organization utilizes the diverse knowledge of the organizational members by selecting and combining their different belief-sets.

The third finding demonstrates that the way complexity acts upon path dependence differs for the learning regimes and ties in closely with the dominance of the individual or mutual learning mechanism in the different learning regimes. While in beneficial learning conditions increasing complexity slows the time to lock-in, in detrimental conditions it accelerates organizational lock-in. The effects of increasing complexity depend on how the different learning processes interact. With a dominant local search mechanism of individual learning and mutual learning acting on similar beliefs, increasing complexity leads to an earlier lock-in. Due to the increasing number of local optima, the individuals get stuck faster. In contrast, increasing complexity for systems with a stronger mutual learning mechanism based on a higher belief variety, raises time to lock-in as complexity distracts the organization from its learning path.

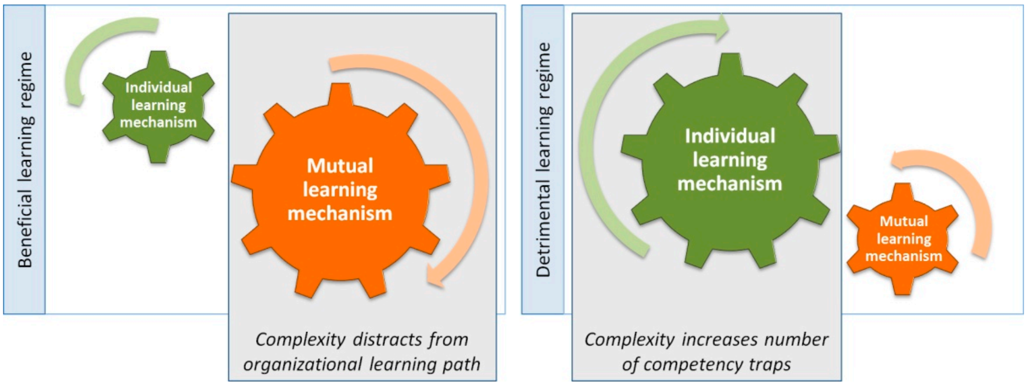


Table 17: The impact of complexity on path-dependent organizational learning

Complexity therefore impacts path dependence in learning in two ways:

- It increases the number of competency traps resulting in a faster lock-in of individual learners.
- In processes of social adaptation, it disturbs the process of aggregating knowledge on the organizational level, thereby slowing down the development of a path.

In interaction, the de-locking potential of both dynamics enables the organization to tackle surprisingly complex problems and lowers the severity of the organizational lock-in.

7.2.2 Environmental Turbulence

The following discussion reflects on the question: How does environmental turbulence influence path-dependent organizational learning?

Environmental turbulence has been highlighted in our study as a relevant condition for path dependence research for different reasons. First, it aggravates the diagnosis of a path. If the environment is turbulent, even an efficient belief-set is bound to be problematic for the organization. Considering environmental turbulence, every stable situation is at least potentially inefficient (Sydow, Schreyögg, & Koch, 2009:704). Environmental change creates a rationality shift in which a previously successful set of beliefs flips into a dysfunctional one. Second, environmental turbulence can interfere with the development of a path. Rationality shifts which occur in the path formation phase can be perceived and counteracted by the organization. Clearly, the timing of rationality shifts influences if and how the organization gets path dependent. Third, because environmental turbulence confronts the organization with a moving target the consequences of the variation and selection processes in the system are bound to show different effects compared to stable environments (Siggelkow & Rivkin, 2005). A turbulent environment points directly to the nature of learning processes as a double-edged sword. In learning, an organization adapts and loses adaptability at the same time. In a turbulent environment, this tension becomes especially obvious as the organization has less time to adapt and similarly has to uphold adaptability.

An important aspect with regard to rationality shifts in the organizational environment is whether we consider actors to have the ability to perceive their environment. In this case, we also have to envisage the actors as possibly struggling to adapt to changes in their environment within their own limited means. Crouch & Farrell (2004:12) incorporate an active actor in their model of Polya urn processes. They claim that *“path dependence theory cannot strictly speaking be used to address actors coping with changes to their environment, because it does not explicitly model that possibility”* (Crouch & Farrell, 2004:6). If actors are modeled as sensors to the environment, it becomes possible that path-dependent trajectories are influenced by exogenously changing environments.

In our model, the passive actors of the mutual learning approach were supplemented by individuals who are capable of learning experientially based on environmental feedback. The difference is a crucial one. Whereas in systems of mere mutual learning, we must assume the organization to be strictly subject to a dynamic leading to lock-in even if timing and scope of change interfere with this dynamic, organizations with active actors are able to generate variety based on perceived environmental changes. Similar to the model of Crouch & Farrell (2004:12-13) and Burgelman's (2002:351-352) argumentation, here it is the environmental change which initiates efforts of the actors to adapt within the path-dependent dynamics which are consistently at work.

In a mere mutual learning model, stripped of active actors, by varying the frequency and scope of change we found the path-dependent dynamic of decreasing variety affected in the following way:

1) As expected, environmental change degrades organizational, or in other words code knowledge, and the average knowledge of the organizational members; the strength of the effect depends on the frequency and scope of change.

2) Environmental change impacting during the development of an organizational path delays the lock-in by disturbing the adaptation at the organizational level.

As depicted in Figure 46, the organization in a turbulent environment here experiences two effects: a strong first order effect of knowledge degradation which directly relates to the frequency and scope of change and the weaker second order effect which acts in the opposite direction and is concentrated on the organizational level.

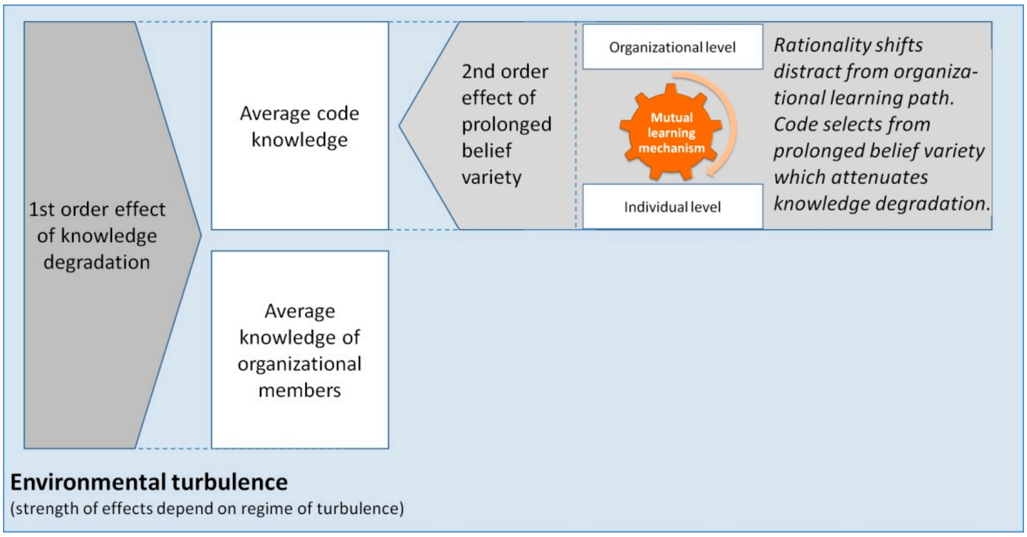


Figure 46: First and second order effect of environmental turbulence in a mere mutual learning model

Even if individual knowledge on average is heavily devalued, the organization benefits from the prolonged belief variety especially in environments which feature strong and frequent changes. Thus, the organization experiences what March (1991:79) called the gains from diversity. Even if the average knowledge of the individuals in the organization declines, the prolonged variety at least in a limited way improves organizational knowledge. However in mere mutual learning, even though timing and scope of change interfere with the dynamic leading to lock-in, after knowledge variety has finally died down, environmental change reduces organizational knowledge until the process represents a random walk (March, 1991:80).

With individuals who act as sensors of the organization to its environment, the situation is different. Here, the actors are not considered to be blind (Ganco & Hoetker, 2008:11) so that learning efforts are triggered by changes in the environment. In contrast to other variation increasing practices, such as personnel turnover (March, 1991; Fang, Lee, & Schilling, 2010), these learning efforts are still bound by the limited cognitive ability of the actors themselves and by the organizational setting which restricts learning to specific areas.

Crouch & Farrell, (2004:22) point out that the present variety in a system influences the effectiveness of adapting to environmental changes. In our case, the effectiveness of individual learning depends on the existing belief variety in the organization. This points to two relevant questions for the impact of turbulence on path dependence: First, if environmental change impacts after the belief variety has died down, is the organization able to counteract path dependence? Second, which results are achieved if change interferes with the learning dynamic?

The following table summarizes the results for environments of different change configuration. First, we discuss the results in which change impacts after the organization has converged on a homogeneous belief-set (low frequency), then we proceed to the results in regimes of frequent change.

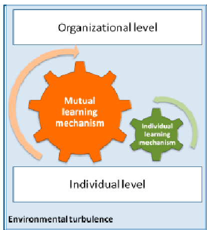
	**Frequency low**	**Frequency high**
Scope low	**Avg. org. knowledge: medium to low** **Avg. belief variety: low** *(After an increase based on inital belief variety, organizational learning success declines with every environmental change before being preserved on a medium to low level.)*	**Avg. org. knowledge: very low** **Avg. belief variety: medium** *(After slight increase based on inital belief variety, organizational learning success drops to a very low level. A medium level of belief variety in the organization is preserved.)*
Scope high	**Avg. org. knowledge: medium** **Avg. belief variety: medium** *(With every environmental change, organizational learning success drops drastically but then recovers not to initial but to a medium level.)*	**Avg. org. knowledge: low** **Avg. belief variety: high** *(Individual learning highly disturbed, but due to high belief variety organizational learning significantly surpasses individual learning.)*

Table 18: Overview of simulation results for different regimes of environmental turbulence

In case of environmental change not interfering with the learning cycle, we found the following: As ascertained above, individual learning introduces variety after every environmental change. Here, the amount of variety introduced by individual learning is influenced by the scope of environmental change. A stronger rationality shift is noticed by more individuals and thus confronts the organization with a stronger stimulus to change.[270] Posen & Levinthal (2012:588; 595-596) in this respect describe an action bias which occurs endogenously in experiential learning when confronted with environmental change. If the organization is able to follow that stimulus depends on the learning conditions, or in other words, the internal processes of selection and alignment determine if the ideas will impact on the organizational level (Burgelman, 2002). The results also indicate that in case of weak changes the organization even with beneficial learning settings is inclined to lose touch with its environment. Here, the organization conducts adaptation within tight boundaries but experiences significant loss of performance. We may argue here in a similar direction as Crouch & Farrell (2004:11) and Pierson (2000:265) that in this case change still occurs but it is tightly bound. North (1990:98-99) in this regard concludes that *"[p]ath dependence is a way to narrow conceptually the choice set (…). It is not a story of inevitability in which the past neatly predicts the future."*

In case environmental change interferes with the learning cycle so that frequent changes impact on the organization, our results show the following: Frequent change interrupts the process of knowledge convergence or in other words the formation of the path. Here, we are again confronted with the double-edged nature of learning. The convergence of knowledge is necessary for the organization to learn. Without the dynamics of selection and alignment, organizational learning is not feasible. Consequently, constant interruption of the organizational learning cycle hinders not only path formation but similarly the development of organizational knowledge in the first place. In highly turbulent environments, we therefore encounter organizations which are paralyzed by environmental change but cannot be considered path dependent.

Figure 47 relates the observed effects to the different mechanisms of learning in the model.

[270] Vergne & Durand (2010:737) in this respect argue that exogenous shocks interfere with a lock-in state.

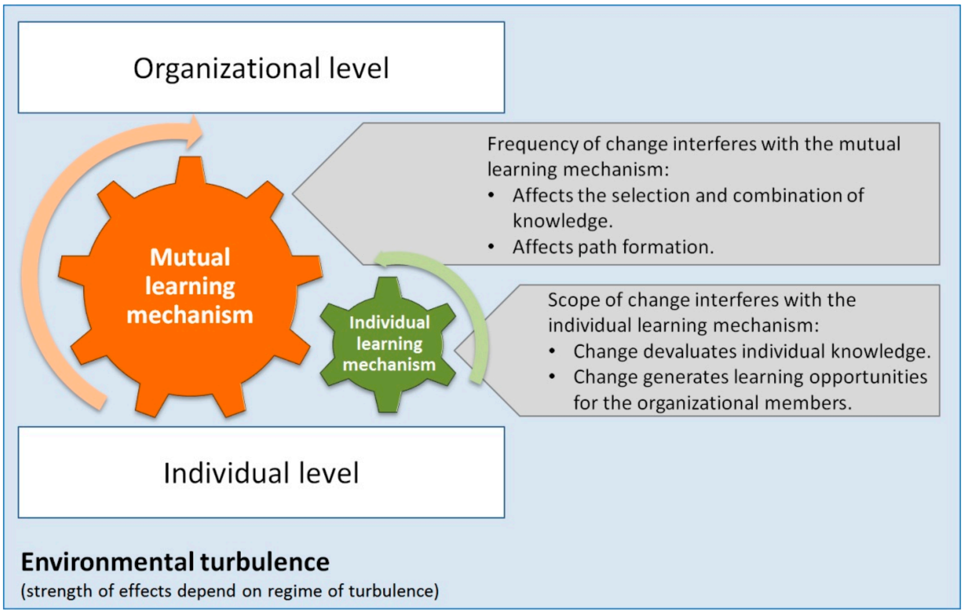


Figure 47: Effects of frequency and scope of change on the individual and mutual learning mechanism

Similar to environmental complexity, turbulence impacts on the two mechanisms in learning in different ways. The interaction of these effects determines the results which will be achieved in environments of varying scope and frequency of change. Whereas frequent changes interfere with the mutual learning mechanism and hamper the selection and combination of valuable solutions, on the individual level in particular strong changes create an imperative to learn.

Pierson (2000:260-261) notes that the character of learning brings about path dependence but similarly learning could be a way to break it. Crouch & Farrell (2004:24-26) build on this argumentation and point out that this is the case in settings where components of a collective agent can learn from each other. With regard to learning in organizations, we highlighted that exploitation at one level can have explorative qualities at another level. However, this interaction between the levels does not enable the organization to completely avoid path dependence but it contributes significantly to the intelligence of the organization at least decreasing the severity of the lock-in. In turbulent environments, individual learning even if bounded to the neighborhood of the organizational belief system serves as a mechanism of bounded adaptation which at least in beneficial learning settings makes the organization able to avoid complete degeneracy.

The interaction between individual and mutual learning and its consequences for organizational behavior in complex and turbulent environments are at the heart of this dissertation. Our core insight refers to the interplay of both dynamics at the different organizational levels. Exploitation at the individual level must be considered exploration at the organizational level whereas exploitation at the organizational level is transformed into exploration at the individual level. Holmqvist (2003; 2004) in a longitudinal case study found evidence of a similar phenomenon between the organizational and the inter-organizational level. He suggests that *"exploitative (…) closure is a form of broadening possible experiences and, as a result, exploitation can become a cause of exploration."* (Holmqvist, 2004:71). Bearing close resemblance to the processes taking place between individual and organizational level, Holmqvist (2003:114-115) finds that a single organization by increasing a specific set of skills creates the basis for inter-organizational exploration. The combination of experiences of single organizations at the inter-organizational level in turn serves to create variety at the organizational level. Framing the impact of the different learning processes on the different levels in terms of their exploitative and explorative qualities sheds light on the two edged nature of learning in organizations. It is this interplay through which the tapering learning path of an organization unfolds.

After discussing the implications of our findings for path dependence theory and research on organizations, in the following chapter we deal with the limitations of our inquiry and point out directions for future research.

7.3 Limitations and Future Research

Our study involves different steps in which we proceed from a theoretical framework to a computational model which subsequently is examined in an experimental phase. In the following section, the theoretical framework and the computational model are analyzed for possible limitations. We will show that some of these limitations open up new research directions which could be dealt with employing the same model or could be considered as possible extensions of our model concentrating on other aspects of organizational learning in complex and turbulent environments.

In the theoretical preliminaries, we provided focus for our research question by specifying the learning mechanism which connects organization and environment as well as the relevant environmental characteristics for our inquiry. Our theoretical framework of path-dependent learning is the result of an analysis of different approaches of organizational learning and defines which elements and interacting processes are considered relevant in our research. Developing a theoretical framework, hence, is a process of structuring and evaluating, of integration and omission. Several of our decisions might be questioned.

Consider, for example, the different levels of the organization. In our framework, we decided to omit the group level. Even if, in our opinion, groups and organizations are concepts which converge (Argote, 2009), research building on a framework purely inspired by Crossan, Lane, & White (1999) would argue differently and probably differentiate between learning processes which focus on interpreting (connecting individual and group level) and integrating (connecting group and organizational level).

Similarly, our theoretical framework differentiates between individual and collective repositories of knowledge and considers the supra-individual component (the code) an essential element of organizational learning (Levitt & March, 1988; Walsh & Ungson, 1991:61; Argote, 2009:9). The assumption that the loci of knowledge in organizations could be anything else than solely the organizational members might be awkward for other researchers who would prefer to consider organizational knowledge simply as an aggregate of individual knowledge (Carley, 1992; Simon, 1991). Researchers arguing in favor of a modular approach would thus be more comfortable with modeling a direct exchange between the organizational members.

With relation to the characteristics of the organizational environment, we identified turbulence as being composed of the frequency and scope of change. Appending further characteristics which detail the impact of turbulence might provide additional differentiation with respect to the effects of environmental turbulence. Suarez & Oliva (2005), for example, characterize turbulence to be defined by its frequency, scope and furthermore its speed and amplitude.

When we transferred our theoretical framework into a computational model, we focused on the dynamics of individual and organizational level learning and kept the representation of the internal organizational context as simple as possible. Our research made use of a crucial advantage of computational modeling compared to other methodological approaches. Computational modeling enables us to show how mechanisms work.[271] While we concentrated on the effects of the external context on the mechanisms of learning we surely underexplored how this interaction is influenced by different organizational settings.[272] In our theoretical framework, these extensions would be reflected in different specializations of the active and the latent context of learning. In our model, we considered the active context to be represented by the abstract supra-individual knowledge repository (the code) whereas the latent context is described by the different paces of learning. We already showed that interpersonal learning or different network structures are mainly moderators of the more abstract learning rates.[273] We therefore consider different configurations of the active context of learning or adding additional mechanisms to the model as the most promising avenues for future research.

With respect to the active context of learning, the organizational code could be framed not to represent an abstract organizational belief system but as the managing group in the organization (Rodan, 2005). An interesting and easy to implement extension to our model would then involve testing the effect of different learning practices or intelligence levels of the managing elite. For example, what would happen if in a path-dependent system the management elite is replaced by new members with random beliefs?

As a matter of fact, power and politics have been acknowledged as impacting the efficiency of organizational learning (Blackler & McDonald, 2000; Coopey & Burgoyne, 2000). Lawrence et al. (2005) more specifically argue that different forms of power are involved in transforming individual learning into organizational level institutions. Addressing different forms of power complicates the dynamics in our model and involves more thorough alterations but can contribute to a better understanding how learning effects interact with an additional mechanism in the internal organizational context. In an easy and efficient way, power in our model

[271] We are grateful to Hart Posen for making this explicit.

[272] In our learning model, this internal organizational context is merely reflected in the different learning paces.

[273] See chapter 4.1.3.

could be implemented as an additional mechanism which influences the costs and benefits which organizational members associate with respective beliefs. The actors in the model could thus be differentiated according to their ability to promote particular beliefs. Whereas the behavior of some agents is supposed to have little social impact, other powerful agents show a high potential to endorse their ideas. Depending on his strength, a leader might have the power to drag the organization into a lock-in state or, on the other hand, to break existing lock-ins.[274]

With respect to power distributions in and between organizations, Holmqvist (2004:72) argues that between levels the transfer of knowledge instead of being a process of copying resembles more a process of social bargaining. Another interesting extension here could alter the exchange between code and organizational members incorporating practices how experience is translated in organizations.

To conclude: simplification, limitations and potential extensions to a model are closely connected issues. First of all, simple models provide us with a clearer picture of the dynamics at work. As our discussion in this chapter reveals, we therefore deliberately excluded many confounding aspects of organizational life. Our model is therefore limited to merely illustrating the effect of basic phenomena: the effects of the context with respect to the dynamics of individual and organizational level learning as outlined in this dissertation. As a consequence, our model offers ample possibilities for extension. As can be rightfully stated for every simulation model but is seldom remarked in the limitation section, adding additional mechanisms and processes to these systems very soon leads to an abundance of effects which are hard to disentangle. Anyone interested in extending this model is therefore well advised to start with a simple setting, considering the influence of the alterations made to the model in a building block approach.

The subsequent chapter concludes this dissertation by giving a brief overall summary.

[274] Please refer to Uotila, Keil, & Maula (2010) how to implement such a mechanism in an NK model.

7.4 Summary and Concluding Remarks

This dissertation aimed at answering the question:

- How does the environmental context influence organizational path dependence?

Research on path dependence has so far largely neglected the effects of the context on the unfolding of path dependence. Most analyses of path dependence simply leave the environmental context out of the picture (David, 1989; Arthur, 1989), or do not inquire in any depth into the effects of specific environmental characteristics (North, 1990; Pierson, 2000). As a consequence, Sydow, Schreyögg, & Koch (2009:701) encourage further research into environmental conditions which enhance or hinder the self-reinforcing mechanisms leading to path dependence.

Our analysis of path dependence research revealed that two important contextual characteristics, complexity and turbulence, have been acknowledged as interacting with the development of paths. However, the analyses fall short in specifying the precise interaction between the mechanism of self-reinforcement and the environmental condition (North, 1990; Pierson, 2000) or neglect the organizational setting (Koch, Eisend, & Petermann, 2009; Crouch & Farrell, 2004).

We argued that the input and output variables of our research - environment and organizational path dependence - are connected by a mechanism of learning. We found that organizational path dependence theory does not provide us with a sufficiently detailed account of the mechanism's elements and processes. Our theoretical framework of path-dependent organizational learning aimed at closing that gap. Building on organizational learning and path dependence literature, we concluded that path dependence in learning is brought about by an imbalance between the adaptive qualities in learning and its rigidifying tendencies. We identified two feedback loops involving different organizational levels to be at the heart of the path-dependent dynamic. At the individual level, learning is depicted as a process of increasing knowledge based on experience, at the organizational level as a process of social adaptation.

The basic properties of our research guided our methodological choice. As our inquiry focused on interacting processes which have to be tested repeatedly in various contextual settings we employed a computational approach. We outlined NK landscapes as a valuable tool to tackle the non-linear nature of path-dependent processes under conditions of complexity and turbulence. After clarifying the suitability of the simulation method for our inquiry, we related existing computational models to our research focus. We approached the models using the central distinction between processes of collective and individual learning which emerged in our theoretical framework. An important aspect of our work here is that we specify in detail the dynamics at work at the different organizational levels. We found that learning processes of social adaptation are best represented in models of mutual learning (March, 1991; Rodan, 2005; Miller, Zhao, & Calantone, 2006; Fang, Lee, & Schilling, 2010). The path-dependent dynamic here is one of decreasing internal belief variety. Individual learning can, in turn, be represented as a process of local search in an NK framework (Rivkin & Siggelkow, 2003; 2006; Siggelkow & Levinthal, 2003; 2006; Siggelkow & Rivkin, 2005; 2006). The path-dependent dynamic here resides in the myopic and incremental nature of the learning process. We argue that path-dependent organizational learning can only be represented by an integration of both dynamics in one model. With respect to the interplay of the dynamics we drew an important conclusion as to the nature of the learning processes on different organizational levels. Individual and organizational level learning both are of exploitative character at their respective level but they have explorative aspects on the other level. It is this interaction which crucially determines organizational behavior in differently complex or turbulent environments.

Based on considerations of the interrelated nature of complexity and bounded rationality, we first argue that in simple environments organizations do not become path dependent. Our experimental results confirm the assumption that complexity is a necessary condition for path dependence in learning. It is not, however, a sufficient condition: the organization deals with complexity surprisingly intelligently as exploitation on one level is transformed into exploration on the other level. Varying the degree of complexity has two effects. Besides increasing the inefficiency of an organizational lock-in, increasing complexity also interferes with the time to lock-in. For the individual learning mechanism it increases the number of competency traps resulting in a faster lock-in in systems where this mechanism is pronounced. On the organizational level the process of knowledge aggregation is disturbed resulting in a longer time to lock-in for systems with a strong mutual learning mechanism.

For turbulent environments we found that if actors are considered to actively learn about their environments, even if this happens in an exploitative way, path-dependent organizational trajectories are influenced by changes in the environment. Strong changes cause greater rationality shifts and a stronger stimulus to adapt. In case of weak environmental changes the organization although showing some variation to its path loses touch with its environment. Frequent changes impede the development of an organizational path and rather have the effect of leaving the organization paralyzed as it is confronted with a constantly moving target.

On the whole, this dissertation illustrates the importance of the context for path-dependent processes. Depending on their properties contexts enhance or hinder path-dependent results. However, the strength of the effects depends on the prevalent dynamic in the system. Different dynamics of self-reinforcement yield different effects. We deliberately kept the model as simple as possible. Our research did not aim at presenting a model which integrates all possible influence factors. Rather, we wanted to keep the model transparent in order to give a precise account of how the basic mechanisms in learning work and interact with the organizational environment.

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APPENDICES

A Overview of Simulation Parameters

Class	Parameter	Comment/Explanation	Variable type
Example			
	int xAxisLabelsToShow	Parameter specifying x-axis in graphical output	
	String space	NK landscape file	
	N	Number of environmental dimensions	CV
	K	Complexity of environment, interaction of dimensions	IV
	int modelruns	Number of runs	CV
	int ticks	Number of ticks	CV
	int pop	Number of agents	CV
	int strategyID	Sets code or network model	not used
	int nettype	Networktype of model	not used
	double[] netstuff	Networkparameters für random and small world networks	not used
	int period	Frequency of change in environment	IV
	double tau	Scope of change	IV
	boolean keepDependenciesOnChange	Determines if dependencies in Nk landscape are kept during change	CV
	double[][] agentProbabilities	Speed of learning of agents	
	Explore	Speed of exploration	IV
	Agents	Speed of learning from contacts/from code	IV
	Code	Speed of learning by code	IV
Model			
	double MAXSCORE	Score of best solution in NK landscape	
	int rounds	Number of ticks	
	ArrayList<agent> agentList	Representation of all agents	
	int netType	Networktype in network model	
	double[] netInfo	Networkparameters für random and small world networks	not used
	int strategy_ID	Sets network or code organization	
	double[][] agentProbabilities	Speed of learning of agents	
	double[] avgScoresRaw	Learning Success	DV
	double[]Heterogeneity	Heterogeneity of solutions	DV
	int[] uniqueAgents	Number of different solutions in organization	DV
	double[]codeScore	Learning Success of Code	DV
	double[] avgScores	avgScoresTransform, transformed learning success	
	double[] maxScoreHistory	Maxscore of NK landscape	
	int x	Frequency of change in environment	
	double t	Scope of change	
	boolean keepDependenciesOnChange	Determines if interactions in NK landscape are kept during change	
	long seed	Seed value for reproduction of specified models	
	Random rand	Random number generator	
Agent/			
Agent_Code	int id	Number to identify agent	
	int[] soln	Solution occupied by agent	
	double cur_score	Score of agent's solution	
	int[] new_soln	Placeholder to handle iterative nature of simulation	
	double new_score	Placeholder to handle iterative nature of simulation	
	int[] test_soln	Placeholder to handle exploration process	
	ArrayList<agent> neighbors	List of neighbors of agent	
	double probabilityExplore	Learning speed exploration	
	double probabilityAgents	Learning speed exchange	
	ArrayList<Double> history_score	Keeps track of score history of agent	
	int numBetterPerf	Number of agents code accesses for learning	CV
	double probabilityCode	Learning speed of code	

Class	Parameter	Comment/Explanation	Variable type
NetObj	int[][] net	Represents the network of agents	
	int numNeighbors	Number of neighbors of agent	
Nkgen	double[] nk	the score list, a very long bit string of size 2^N	
	int n	Number of environment dimensions	
	int k	Complexity of environment, interaction of dimensions	
	int[][] links	Stores the links of the NK landscape	
Nkspace	double max	Maxscore of NK landscape	
	double[] scores	the score list, a very long bit string of size 2^N	

Table 19: Simulation parameters in order of appearance in program code[275]

[275] The colors relate to the type of variable as used in the variable overview in chapter 4.3.

B Source Code of the Simulation Model

In the following section, we posted the different java classes of the computational model which basically describe the NK landscape, the agent behavior, their network ties, and the experimental setting. The model defines different organizational settings. We excluded classes which are not relevant for an organizational model in which beliefs are exchanged via an organizational code. Model.java still contains objects and methods which refer to additional settings and strategies which we did not use in the experiments reported in this dissertation.

NK_gen.java

```java
import java.io.*;

/**
 * The code was originally designed for Lazer, David and Allan Friedman.
 * "The Network Structure of Exploration and Exploitation."
 * Administrative Science Quarterly, 52:4. 2007.
 * Licensed under Creative Commons Attribution-Share Alike CC(2007),
 * http://creativecommons.org/licenses/by-nc-sa/3.0/us/
 * Changed and adapted by Seidel, Eva.
 * "Path Dependence and the Environmental Context" PhD,
 * Free University of Berlin.
 * This code generates an NK space (Kauffman 1992 in the form of an 2^n string
 * for an n-dimensional NK space.
 * An NK space works like this: each point in an n-length bit string has k
 * dependency links. The score of each link depends on k other bits, so there
 * are 2^K possible scores for each bit.
 * The score of an NK string is the normalized sum of each bit contribution.
 */


public class NK_gen {

    double[] nk;  //the score list, a very long bit string of size 2^n
    int n;        //model param - bit length
    int k;        //model param - epistatis or ruggedness of landscape
    public int numMax;
    private int[][] links;

    public NK_gen(int n_, int k_) {
        n = n_;
        k = k_;
        nk = new double[(int) Math.pow(2, n)];  //2^n scores in an n space
    }


    // THE MAIN FUNCTION
    /* 1) Create the matrix of random links between each node
     * 2) Create a score for each possible combination of nodes
     * 3) Walk the entire space, filling in the appropriate score
     */
    public void build_space(){
        int size = nk.length;
        int numscores = (int) Math.pow(2, k + 1);
        //Links between the genes, including the gene itself
        links = new int[n][k + 1];
        //each possible mask combo gets a score
        double[][] scores = new double[n][numscores];

```

```
        //fill the links
        for (int i = 0; i < n; i++) {
            links[i][0] = i;
            for (int j = 1; j < k + 1; j++) {
          //fills rest of link lists with random links to rest of gene
                links[i][j] = (int) (Math.random() * n);
            }
        }

        //fill the scores for every gene
        //NOTE that the scores can be randomly filled
        //because they are accessed to mimic epistatic selection
        for(int i = 0; i < n; i++) {
            for(int j =0; j < numscores; j++) {
              //each different gene combination gets a different score
               //score drawn from uniform distribution 0-1
                scores[i][j] = Math.random();
            }
        }
        //a single reusable mask to look at the genespace
        int[] mask = new int[k+1];
        //Walk through entire gene-space, filling in scores for each gene
        for(int s = 0; s < size; s++) {  //s is for Space
            //create a binary string for this gene combo
            int[] id = intToBin(s);


            double temp_score = 0;
            for(int g = 0; g < n; g++) {  //g is for gene
               //fill the mask
               for(int m = 0; m <= k; m++) {
                   //fill the mask with the link-specified parts of the space
                  mask[m] = id[links[g][m]];   //mask should be binary
                }
                //add the score of each gene in the genome
                //index score using the mask
                temp_score += scores[g][binToInt(mask)];
            }
            //set the score of that genome
            //the average across all the genes in the genome
            nk[s] = temp_score/n;
        }
    }

    public double[] getNK() {
        return nk;
    }

    private double getMaxScore() {
      double max = -1;
      for (int i=0;i<nk.length;i++){
         if (nk[i]>max){
            max = nk[i];
         }
      }
      return max;
    }

    //method to be accessed when comparing NK spaces
    public double getMaxScoreExample() {
      double max = -1;
      for (int i=0;i<nk.length;i++){
         if (nk[i]>max){
            max = nk[i];
         }
      }
      return max;
    }

    //prints the NK to a file
```

```
    /* FORMAT *.nk:
    * NOTE that it is not human-readable
    * Datum 1: n  -should be read to determine how long the datastruct is to be
    * Datum 2: k  -double check the appropriate k
    * Data 3-2^n+2 -the NK file
    */
    public void write_to_file(String title) throws IOException {
        title = (title+".nk");  //put the file suffix on to identify it
        int size = nk.length;

        DataOutputStream out = new DataOutputStream(new
        BufferedOutputStream(new FileOutputStream(title)));
        out.writeInt(n); //keep NK space data with file.
        out.writeInt(k); //keep NK space data with file.
        out.writeDouble(getMaxScore());

        //write the scores
        for(int i=0; i < size; i++) {
         out.writeDouble(nk[i]);
        }

        //also write the dependencies
        out.writeInt(links.length);
        for (int i = 0; i < links.length; i++) {
            out.writeInt(links[i].length);
               for (int j = 0; j < links[i].length; j++) {
                  out.writeInt(links[i][j]);
            }
        }
        out.close();
    }

/******************  HELPER FUNCTIONS *********************/
    //Takes a number, returns an array representing its binary value

    public int[] intToBin(int num) {
        int[] bin = new int[n];
        //start with the highest bit
        for(int i = n-1; i >= 0; i--) {
         //bitshift 1 over and compare with the power of 2
            if(((1 << i) & num) != 0) {
               //write things right to left
                bin[n-1-i] = 1;
            }
            else {
                bin[n-1-i] = 0;
            }
        }
        return bin;
    }

    public int binToInt(int[] bin) {
        int t = bin.length;      //should be k+1
        int num = 0;
        int coef = 0;
        for(int i = 0; i < t; i++ ) {
            coef = (int)Math.pow(2, (t-i-1));
            num += bin[i] * coef;
        }
        return num;
    }

    //Computes the number of local maxima in the space
    public int getNumPeaks() {
      int numMax = 0;
      //for each point in the space
      for(int i = 0; i < nk.length; i++) {
         int[] orig = intToBin(i);
         int max_flag = 0;  //reset flag
         //for each of the n possible variations
```

```
        for(int j = 0; j < n; j++) {
           int[] neighbor = new int[n];
           //copy the original
           neighbor = (int[]) orig.clone();

           int bit  = (orig[j]+1) % 2;
           neighbor[j] = bit; //alter one bit
           //compare scores
           if(nk[binToInt(neighbor)] >= nk[i]) {
              //if neighbor is bigger, not a max
              max_flag = 1;
           }
        }
        if(max_flag==0) numMax++;
     }
     return numMax;
  }
```

NKSpace.java

```
import java.io.*;
import java.util.Random;

/**
 * The code was originally designed for Lazer, David and Allan Friedman.
 * "The Network Structure of Exploration and Exploitation."
 * Administrative Science Quarterly, 52:4. 2007
 * Licensed under Creative Commons Attribution-Share Alike CC(2007),
 * http://creativecommons.org/licenses/by-nc-sa/3.0/us/
 * Changed and adapted by Seidel, Eva
 * "Path Dependence and the Environmental Context" PhD,
 * Free University of Berlin.
 * Includes a function to change NKspace according to specified parameters
 * tau and x.
 */

public class NKSpace extends fitnessSpace {
   private int n;
   private int k;
   public double max;
   public double[] scores;
   private Random random;
   int numMax;
   private int[][] links;
   NK_gen gen;

   //whether the dependencies between different
   //solutions should be kept on a landscape change
   private boolean keepDependenciesOnChange;

   //Loads the space from  file
   //called with a filename to create an object to keep the space local
   public NKSpace(String file, boolean _keepDependenciesOnChange) {
      this(file,_keepDependenciesOnChange,new Random());
   }
   public NKSpace(String file, boolean _keepDependenciesOnChange, Random rand)
{
      spaceFile = file;
      keepDependenciesOnChange = _keepDependenciesOnChange;
      random = rand;

      //load score space
      try {
         DataInputStream in = new DataInputStream(new
         BufferedInputStream(getClass().getResourceAsStream(file)));
         //get n from the NK file
         //while copying old files
         n = in.readInt();
```

```
         k = in.readInt(); //get k from the NK file
         max = in.readDouble();

         scores = new double[(int)Math.pow(2, n)];

         //read the scores
         for(int i=0; i < (int)Math.pow(2, n); i++) {
            //import the entire file
            scores[i] = in.readDouble();
         }
         //read the dependencies
         links = new int[in.readInt()][];
         for (int i = 0; i < links.length; i++) {
            links[i] = new int[in.readInt()];
            for (int j = 0; j < links[i].length; j++) {
               links[i][j] = in.readInt();
            }
         }
      }
      catch (IOException e) { System.out.println (" IOexception =" + e );;}
   }

   public int getN() {
      return n;
   }

   public int getK() {
      return k;
   }

   //public lookup function to get the score for an agent
   public double getScore(int point) {
      return scores[point];
   }

   //find the highest score in a space for scoring reasons
   public double getMax() {
      return max;
    }

   //find the highest score in a space for scoring reasons
   public double findMax() {
      double max = -1.0;
      for (int i = 0; i < scores.length; i++) {
         if (scores[i] > max)
            max = scores[i];
      }
      return max;
   }

   //Changes the landscape
   public void changeLandscape(double _tau) {
        int size = scores.length;
        //number of scores for every gene in combination
        //with interacting genes
        int numscores = (int) Math.pow(2, k + 1);
        //each possible mask combo gets a score
        double[][] comboScores = new double[n][numscores];

       //fill the links between the bits
       //if links shouldn't be kept, get new ones
        if (!keepDependenciesOnChange) {
         for (int i = 0; i < n; i++) {
            links[i][0] = i;
            for (int j = 1; j < k + 1; j++) {
               //fills rest of link lists with random links
               //to rest of gene
               links[i][j] = (int) (random.nextDouble() * n);
            }
         }
```

```
        }

        //fill the scores
        //NOTE that the scores can be randomly filled
        //because they are accessed to mimic epistatic selection
        for (int i = 0; i < n; i++) {
         //numscores = possible combinations between gene and
         //interacting genes
            for(int j =0; j < numscores; j++) {
                //each different gene combination gets a different score
               //score drawn from uniform distribution 0-1
               comboScores[i][j] = random.nextDouble();
            }
        }

        //a single reusable mask to temporarily store each bit’s averaged score
        int[] mask = new int[k+1];
        //walk through entire gene-space, filling in scores for each bit
        //get the decimal values of all bit combos in 2^n
        //size  is number of solutions in NK space
        for(int s = 0; s < size; s++) {
        //turn it into its bit combo (which the agents call 'solution')
        int[] id = intToBin(s);

            double temp_score = 0;
            //walk through the bits
            for(int b = 0; b < n; b++) {
               //fill the mask with the link-specified parts of the space
                for(int m = 0; m <= k; m++) {
                  //mask should be binary
                     mask[m] = id[links[b][m]];
                }
                 //add the score of each gene in the bit combo
                //index score using the mask
                temp_score += comboScores[b][binToInt(mask)];
            }
            scores[s] = (scores[s] * _tau) + ((temp_score/n) * (1.0 - _tau));
        }
    }

    /*****************  HELPER FUNCTIONS ********************/

    //Takes a number, returns an array representing its binary value
    public int[] intToBin(int num) {
        int[] bin = new int[n];
      //start with the highest bit
        for(int i = n-1; i >= 0; i--) {
         //bitshift 1 over and compare with the power of 2
            if(((1 << i) & num) != 0) {
               //write things right to left
                bin[n-1-i] = 1;
            }
            else {
                bin[n-1-i] = 0;
            }
        }
        return bin;
    }

    public int binToInt(int[] bin) {
        int t = bin.length;      //should be k+1
        int num = 0;
        int coef = 0;
        for(int i = 0; i < t; i++ ) {
            coef = (int)Math.pow(2, (t-i-1));
            num += bin[i] * coef;
        }
        return num;
    }
  }
```

netObj.java

```
/**
 * The code was originally designed for Lazer, David and Allan Friedman.
 * "The Network Structure of Exploration and Exploitation."
 * Administrative Science Quarterly, 52:4. 2007
 * Licensed under Creative Commons Attribution-Share Alike CC(2007),
 * http://creativecommons.org/licenses/by-nc-sa/3.0/us/
 * Changed and adapted by Seidel, Eva
 * "Path Dependence and the Environmental Context" PhD,
 * Free University of Berlin.
 * Defines the network structure for the simulation.
 * Note that the code model is supposed to run on a FULL network
 */
public class netObj {
  int[][] net;
  Random randGen;

  public netObj(int pop, Random rand) {
     randGen = rand;
     net = new int[pop][pop];
     //zero out the network
     for(int i = 0; i < pop; i++) {
        for(int j = 0; j < pop; j++) {
           net[i][j] = 0;
        }
     }
  }

  public netObj(int pop) {
     this(pop, new Random());
  }

  //a fully connected network
  public void setFullNet() {
     for (int i = 0; i < net[0].length; i++) {
        //Since links are symmetric, can halve the search space
        for (int j = 0; j < i; j++) {
           if(j != i) { //no self-referencing
              net[i][j] = 1;
              net[j][i] = 1;
           }
        }
     }
  }
```
[276]

[276] netObj.java contains additional methods for creating different network types. These are not reported here, since they are not used for the results reported in this dissertation.

agent.java

```
import java.util.*;

/**
 * The code was originally designed for Lazer, David and Allan Friedman.
 * "The Network Structure of Exploration and Exploitation."
 * Administrative Science Quarterly, 52:4. 2007
 * Licensed under Creative Commons Attribution-Share Alike CC(2007),
 * http://creativecommons.org/licenses/by-nc-sa/3.0/us/
 * Changed and adapted by Seidel, Eva
 * "Path Dependence and the Environmental Context" PhD,
 * Free University of Berlin.
 * The agent object controls agent local agent behavior in the simulation.
 * The meat of the agent's behavior occurs in the decision function,
 * which determines which action to take.
*/

 public class agent implements Comparable<agent> {
   //Each agent has a unique ID
   protected int id;
   //the soln is the current solution occupied by the agent
   //in the problem space.
   //soln is kept as a binary string except when a lookup is required.
   protected int[] soln;
   //the score of the current solution, corresponding to the agents' soln.
   protected double cur_score;
   //placeholder used to handle the iterative nature of the simulation.
   protected int[] new_soln;
   //placeholder used to handle the iterative nature of the simulation.
   protected double new_score;
   protected int[] test_soln;
   protected model model;
   protected Random randomGen;
   //list of network connections.
   public ArrayList<agent> neighbors = new ArrayList<agent>();
   protected double probabilityExplore;
   protected double probabilityAgents;


   /********* SETUP functions  ***********/

    // Random starting points for the agents
    public agent(int n, int id_, double[] probabilities, model _model, Random
    _random) {

      randomGen = _random;
      soln = new int[n];
         randomSoln();
         new_soln = soln;
         id = id_;
         model = _model;

         probabilityExplore = probabilities[0];
         probabilityAgents = probabilities[1];
    }

    // Sort agent array
    public int compareTo(agent a) {
      if( this.cur_score > a.cur_score )
            return -1;
        if( this.cur_score < a.cur_score )
            return 1;
        return 0;
    }

    //fills the soln with a random string
    public void randomSoln() {
        for(int i = 0; i < soln.length; i++) {
```

```
            soln[i] = (int)(randomGen.nextDouble() * 2);
        }
     }


   /*****  INTERFACE functions *******/

   public void setScore(double score) {
     cur_score = score;
     new_score = score;
   }

   public double getScore() {
     return cur_score;
   }

   //Allows other agents to access the soln of this agent.
   public int getPoint() {
     return binToInt(soln);
   }

   public int[] getSoln() {
     return soln;
   }

   //After every agent has acted, the effects of these
   //actions are made permanent.
   public void update() {
     soln = new_soln;
     cur_score = model.space.getScore(binToInt(soln));
   }

   /******** DECISION FUNCTIONS CODE AND AGENTS *******/

  //EXPLORATION
  //Agents search the NK landscape
  //All decision functions are called by the base model.
   public void explore(int clock, NKSpace space) {
     explore(space); //take NK solution if better
     update();
   }

  //LEARNING FROM NEIGHBORS
  //Agents identify neighbors that perform better and
  //takes from them the most common bits
   public void neighborlearn (int clock) {

     new_soln = this.soln.clone();
     //initializing target array to sort agents according to performance
     agent[] target = new agent[neighbors.size()];

     //get all neighbors in target array
     for(int i = 0; i < neighbors.size(); i++) {
             target[i] = (agent) neighbors.get(i);
       }
     Arrays.sort(target); //sort target array

     if (this.neighbors.size()!= 0 && target[0].cur_score > this.cur_score){

        int [] betterNeighborSoln = target[0].soln;
        new_soln = approachBetterNeighbor(soln, betterNeighborSoln);
     }
   }


  /******* action execution functions **********/

  //Explore NK
  //check to see if changing a single bit of the current point
  //produces an improved score
```

```
    //If it does, update, otherwise do nothing
    public void explore (NKSpace space) {
       double random = randomGen.nextDouble();

       if (probabilityExplore > random){

             int bit = (int) (randomGen.nextDouble()* soln.length);
             //make a clean copy
             test_soln = (int[]) soln.clone();
             //experiment by shifting the bit
             test_soln[bit] = (soln[bit] +1) % 2;
          //find experimental score
          double testScore = space.getScore(binToInt(test_soln));
          if(testScore > cur_score) {
             new_soln = test_soln;
             //update the score to signal transition
             new_score = testScore;
          }
          else{
             new_soln = this.soln;
          }
       }
     }

    //Determines the array which contains the most common bits
    public int [] determineMostCommonBitArray (ArrayList<agent> a){
       //initializing array which shows the most common bit
       int [] mostCommonBitArray = new int[soln.length];
       int [] uniqueBits = determineUniqueBitsOne(a);

       for (int k = 0; k < soln.length; k++) {

          if (uniqueBits[k] > a.size()-uniqueBits[k]) {
             mostCommonBitArray[k] = 1;
          }
          else {
             if (uniqueBits[k] == a.size()-uniqueBits[k]) {
                mostCommonBitArray[k] = this.soln[k];
             }
             else {
                mostCommonBitArray[k] = 0;
             }
          }
       }
       return mostCommonBitArray;
    }

    //Determine frequency of bit 0 or 1 at every position of soln
    //for all agents in betterPerfomer Array
    public int [] determineUniqueBits (ArrayList<agent> a) {
       int[] uniqueBits = determineUniqueBitsOne(a);

       for (int k = 0; k < soln.length; k++) {

          if (uniqueBits[k] < a.size()-uniqueBits[k]) {
             uniqueBits[k] = a.size()-uniqueBits[k];
          }
       }
       return uniqueBits;
    }

    //Determines frequency of bit 1 at every position of soln
    //for all agents in betterPerfomer Array
    public int [] determineUniqueBitsOne (ArrayList<agent> a) {
       //initializing array which shows the frequency of 1 and 0
       //in solution of best performers, e.g. [2 5 7 12 1 0 9 6]
       int[] uniqueBits = new int[soln.length];

       for (int l = 0; l < a.size(); l++){
          for (int j = 0; j < soln.length; j++) {
```

```
            if (a.get(l).soln[j] == 1) {
               uniqueBits[j]++;
            }
         }
      }
      return uniqueBits;
   }

   //Agents approach solutions of betterPerformers
   public int [] approachBetterNeighbor (int[] source, int[] destination) {
      int[] result = (int[]) source.clone();
      double random;

      for(int i = 0; i < destination.length; i++){
         random = randomGen.nextDouble();

         if(destination[i] != result[i] && probabilityAgents > random) {
            result[i] = destination[i];
         }
      }
      return result;
   }
   public int id() { return id; }


    /***********  HELPER functions  ************/

   //determines, whether an int array contains a certain int value
   public static boolean intArrayContains(int[] array, int value) {
      boolean contains = false;
      for (int i = 0; i < array.length; i++) {
         if (array[i] == value) {
            contains = true;
            break;
         }
      }
      return contains;
   }

    //converts the binary-string solution to a long for easy score lookup.
    public int binToInt(int[] bin) {
        int t = bin.length;      //should be k+1
        int num = 0;
        int coef = 0;
        for(int i = 0; i < t; i++ ) {
            coef = (int)Math.pow(2, (t-i-1));
            num += bin[i] * coef;
        }
        return num;
    }
}
```

agentCode.java

```
import java.util.ArrayList;
import java.util.Arrays;
import java.util.Random;

/**
 * Establishes code model consisting of an org code and a number of agents.
 * Runs only on a FULL network, as the code must be connected to all agents.
 * Agent 0 is the code.
 * Agent_CODE object refers to agent to set parameters.
 */

 public class agent_CODE extends agent implements Comparable<agent> {
   //size of the group the code accesses for learning
```

```
    protected int numBetterPerf = 5;
    protected double probabilityCode;


    /********* SETUP functions  ***********/

     // Random Starting points, constructor initializes member variables
     public agent_CODE (int n, int id_, double[] probabilities, model
      _model,Random _random) {

       //call super constructor
       super(n, id_, probabilities, _model, _random);
       probabilityCode = probabilities[2];
     }

    /******** DECISION FUNCTIONS CODE AND AGENTS *******/

    //LEARNING BY THE CODE
    //Code is represented by Agent 0
    //Code identifies the best performers and takes from them the bits
    //which are held by the majority of the best performers.

     public void codelearn(int clock) {

       new_soln = this.soln.clone();
       ArrayList<agent> betterPerf = new ArrayList<agent>();
       //initializing target array to sort agents according to performance
       agent[] target = new agent[neighbors.size()];

       //get all neighbors in target array
       for(int i = 0; i < neighbors.size(); i++) {
               target[i] = (agent) neighbors.get(i);
       }
       Arrays.sort(target); //sort target array
       //if numBetterPerf is specified
       for(int i = 0; i < numBetterPerf; i++){
             betterPerf.add(target[i]);
       }

       if (betterPerf.size() == 0){
          new_soln = this.soln.clone();
       }
       else {
          int [] betterNeighborSoln = this.soln.clone();
          new_soln = approachBetterNeighbor(betterPerf, soln,
          betterNeighborSoln);
          update();
       }
     }

     //SOCIALISATION
     //Agents approach solution of the Code
     public void socialisation(int clock) {

       int[] codeSoln = neighbors.get(0).soln.clone();//copy code soln

       //Agent approaches codesoln according to specified parameters
       new_soln = approachCode(soln, codeSoln);
       update();
    }

    //CODE approaches solutions of betterPerformers
    public int [] approachBetterNeighbor (ArrayList<agent> numBetterNeighbors ,
    int[] source, int[] destination) {
       int[] result = (int[]) source.clone();
       double random;
       destination = determineMostCommonBitArray(numBetterNeighbors);

       if (intArraysEqual(result, destination)){
          return result;
```

```
      }
      else
         for(int i = 0; i < destination.length; i++){
            random = randomGen.nextDouble();

            if(destination[i] != result[i] && probabilityCode > random) {
               result[i] = destination[i];
            }
         }

         return result;
   }

   //Every bit of CODE soln is taken by the agents according to
   //prbabilityAgents
   protected int[] approachCode(int[] source, int[] destination) {
      //make a clean copy
      int[] result = (int[]) source.clone();
      double random;
         if (intArraysEqual(result, destination))
            return result;
         else
            for(int i = 0; i < destination.length; i++) {
            random = randomGen.nextDouble();

               if(destination[i] != result[i] && probabilityAgents > random) {
                  result[i] = destination[i];
            }
      }
         return result;
   }
}
```

model.java

```
import java.util.ArrayList;
import java.util.Random;
import java.io.*;

/**
 * The code was originally designed for Lazer, David and Allan Friedman.
 * "The Network Structure of Exploration and Exploitation."
 * Administrative Science Quarterly, 52:4. 2007
 * Licensed under Creative Commons Attribution-Share Alike CC(2007),
 * http://creativecommons.org/licenses/by-nc-sa/3.0/us/
 * Changed and adapted by Seidel, Eva. "Path Dependence and the Environmental
 * Context" PhD, Free University of Berlin.
 * Sets up the basic run of a single world
 * The model is called with the key variable specifications for the agents
 * behavior, and the type of organizations (code, informal) in which
 * they will operate, as well as the NK space.
 * The agent object controls agent local agent behavior in the simulation.
 * Each agent maintains a list of its network ties and its current location in
 * the problem space. A set of flags govern its behavior.
 * The agent refers to the global NKSpace object to determine score.

 */

 public class model {

   NKSpace space;
   NK_gen gen;

   int modelID;

   int pop;
   double MAXSCORE;
```

```
    int numPeaks;
    int rounds;
    int numMax;

    //internal vars
    ArrayList<agent> agentList;

    //network Constants
    final int LINE = 1;
    final int FULL = 2;
    final int RAND = 3; //need a network parameter of density
    final int SMAL = 4; //need a network parameter of small-worldness
    private int netType;

    //agent strategies constants
    final int AGENT = 1;
    final int INFOM = 2;
    final int CODE = 3;
    public int strategy_ID;

    double[] netInfo;
    double[][] agentProbabilities;

    // Convergence Horizon is the length of this array
    // (using 5 as standard)
    //tracks number of agents across turns
    int[] convergeHistory = new int[5];

    // single model history
    public int tickCounter = 0;
    double[] avgScores = null;
    int[] uniqueAgents = null;
    double[] avgScoresRaw = null;
    private double[] maxScoreHistory = null;
    double[]codeScore = null;
    double[]heterogeneity = null;
    //several models history
    double [] modelAvgScores;
    double [] modelAvgScoresRaw;
    double [] modelCodeScore;
    double [] modelUniqueAgents;
    double [] modelMaxScoreHistory;
    double [] modelHeterogeneity;

    // every x ticks every score will change as follows:
    //new score = old score * t + random score * (1 - t)
    //(Siggelkow, Rivikin 2005)
    private int x = -1;
    private double t = 1.0;

    private boolean keepDependenciesOnChange;

    public long seed;
    public long seed() { return seed; }
    private Random rand;


    /***************  SETUP *********************/
    // load the model with the appropriate datastructures
    /* numAgents - population
     * nkfile- file containing NK info
     * nettype - predefined into for what type of network
     * netInfo - holder of additional info for network
     * differentiates between code and informal model(without code)
     * x - amount of ticks to be performed for a landscape change
     * (set -1 for a constant landscape)
     * tau - intensity of a landscape change
     * agentProbabilities - matrix of probabilities for each agent or code
     */

```

```
    public model(int _modelID, String _space, int numAgents, int nettype,
          double netInfo[], double[][] agentProbabilities, int _rounds, int
          _period, double _tau,  boolean _keepDependenciesOnChange, int
          strategyID) {
       this(_modelID, _space, numAgents, nettype, netInfo, agentProbabilities,
       _rounds, _period, _tau, _keepDependenciesOnChange, strategyID,
       System.currentTimeMillis());
    }
    public model(int _modelID, String _space, int numAgents, int nettype,
    double netInfo[], double[][] agentProbabilities, int _rounds, int _period,
    double _tau, boolean _keepDependenciesOnChange, int strategyID, long _seed)
    {

       seed = _seed;
       rand = new Random(seed);
       keepDependenciesOnChange = _keepDependenciesOnChange;

       //load the space & space data
       space = new NKSpace(_space, _keepDependenciesOnChange, rand);
       int n = space.getN();
       MAXSCORE = space.getMax();
       pop = numAgents;
       netType = nettype;
       this.netInfo = netInfo;
       this.agentProbabilities = agentProbabilities;
       rounds  = _rounds;
       x = _period;
       t = _tau;
       strategy_ID = strategyID;
       modelID = _modelID;

       //Create agent array
       agentList = new ArrayList<agent>();
             switch (strategyID) {

       case AGENT:
          for (int i = 0; i < pop; i++) {
             //creates new agent object
             agent a = new agent(n, i, agentProbabilities[i],
                                  this, rand);
             // set the initial score
             a.setScore(space.getScore(a.getPoint()));
             agentList.add(a);
          }
          break;

       case INFOM:
          for (int i = 0; i < pop; i++) {
              agent_INFORMAL_MAJORITY_RULE a = new agent_INFORMAL_MAJORITY_RULE
             (n, i, agentProbabilities[i], this, rand);
             // set the initial score
             a.setScore(space.getScore(a.getPoint()));
             agentList.add(a);
          }
          break;

       case CODE:
          if (nettype != FULL) {System.out.println("Wrong nettype for CODE
          model");}
          for (int i = 0; i < pop; i++) {
             //creates new agent object
             agent_CODE a = new agent_CODE(n, i, agentProbabilities[i], this,
             rand);
             // set the initial score
             a.setScore(space.getScore(a.getPoint()));
             agentList.add(a);
          }
          break;
       }

```

```
      //create the network - use algs defined in netObj.java
      netObj net = new netObj(pop, rand);
      switch(nettype) { //select which type of network
      case LINE:
                  net.setLinearNet();
                  break;
         case FULL:
                  net.setFullNet();
                  break;
         case RAND:
            net.setRandProbNet(netInfo[0]);
            break;
         case SMAL:
            net.setSmallWorldRewireNet((int)netInfo[0]);
            break;
      }
      // map the agent connections into the network
      assignNeighbors(net);

      this.run();
   }


   /*************** EXECUTION FUNCTIONS ******************/
   public void run() {

      avgScores = new double[rounds+1];
      avgScoresRaw = new double[rounds+1];
      codeScore = new double [rounds+1];
      uniqueAgents = new int[rounds+1];
      maxScoreHistory = new double[rounds+1];
      heterogeneity = new double [rounds+1];

      //generates Output Variables for tick 0
      avgScores[0] = avgPopScoreWoCode(); //for code model
      avgScoresRaw[0] = avgPopScoreRawWoCode(); //for code model
      uniqueAgents[0] = numUniqueAgents();
      codeScore[0] = codeScore();
      maxScoreHistory[0] = MAXSCORE;
      heterogeneity[0]= heterogeneityPop();

      for(tickCounter = 1; tickCounter <= rounds; tickCounter++) {

         //changes the landscape every x ticks
         if (x > 0 && tickCounter > 1 && tickCounter % x == 1) {
            space.changeLandscape(t);

            //find new max
            space.max = space.findMax();
            MAXSCORE = space.getMax();

            //get new scores for the agents
            for (agent a : agentList) {
                  a.setScore(space.getScore(a.getPoint()));
            }
          }
            switch (strategy_ID) {

            case AGENT:
               //update the agents
               exploreAgents(tickCounter);
               learnNeighbor(tickCounter);
               updateAgents(tickCounter);
               break;

            case INFOM:
               //update the agents
               exploreAgents(tickCounter);
               learnNeighbor(tickCounter);
               updateAgents(tickCounter);
```

```
               break;

            case CODE:
               //update the agents
               exploreAgents(tickCounter);
               learnCode(tickCounter);
               socialisationAgents(tickCounter);
               break;
            }

         //update history
         switch (strategy_ID) {
         case AGENT:
            avgScores[tickCounter] = avgPopScore();
            uniqueAgents[tickCounter] = numUniqueAgents();
            avgScoresRaw[tickCounter] = avgPopScoreRaw();
            codeScore[tickCounter] = codeScore();
            maxScoreHistory[tickCounter] = MAXSCORE;
            heterogeneity[tickCounter] = heterogeneityPop();
            break;

         case INFOM:
            avgScores[tickCounter] = avgPopScore();
            uniqueAgents[tickCounter] = numUniqueAgents();
            avgScoresRaw[tickCounter] = avgPopScoreRaw();
            codeScore[tickCounter] = codeScore();
            maxScoreHistory[tickCounter] = MAXSCORE;
            heterogeneity[tickCounter] = heterogeneityPop();
            break;

         case CODE:
            avgScores[tickCounter] = avgPopScoreWoCode();
            uniqueAgents[tickCounter] = numUniqueAgents();
            avgScoresRaw[tickCounter] = avgPopScoreRawWoCode();
            codeScore[tickCounter] = codeScore();
            maxScoreHistory[tickCounter] = MAXSCORE;
            heterogeneity[tickCounter] = heterogeneityPop();
            break;
         }
      }
   }

   public String getNetType() {
      switch (netType) {
         case 1:
            return "line";
         case 2:
            return "full";
         case 3:
            return "random_"+netInfo[0];
         case 4:
            return "smallworld_"+netInfo[0];
         default:
            return "unknown";
      }
   }

   public String getStrategyID() {
      switch (strategy_ID) {
         case 1:
            return "INF Tourn";
         case 2:
            return "INF Maj";
         case 3:
            return "CODE";
         default:
            return "unknown";
      }
   }

```

```
    public String getEnvironmentVariables() {
       return +t+"_"+x+"_N_"+space.getN()+"_K_"+space.getK();
    }

    public String getAgentProbabilities() {
       return "expl_"+agentProbabilities[0][0]+"agents_"+
       agentProbabilities[0][1]+"code_"+agentProbabilities[0][2];
    }

    public void printEvolution() {
       System.out.println("[tick]  [learningSuccess]  [codeScore]
       [uniqueSolutions]  [heterogeneity]  [avgScores]  [maxScore]");
       for (int i = 0; i <= rounds; i++) System.out.println("tick "+i+":
       "+avgScoresRaw[i]+"  "+codeScore[i]+ "   "+uniqueAgents[i]+"
       "+heterogeneity[i]+"   "+avgScores[i]+"   "+maxScoreHistory[i]);
    }

    //store output parameters of the models in arrays
    public double [] addAvgScores (double[] sumAvgScores) {
       double [] modelAvgScores = (double[]) sumAvgScores.clone();

          for(int i = 0; i < rounds+1; i++){
             modelAvgScores [i] += avgScores[i];
          }
          return modelAvgScores;
    }

    public double [] addAvgScoresRaw (double[] sumAvgScoresRaw) {
       double [] modelAvgScoresRaw = (double[]) sumAvgScoresRaw.clone();

          for(int i = 0; i < rounds+1; i++){
             modelAvgScoresRaw [i] += avgScoresRaw[i];
          }
          return modelAvgScoresRaw;
    }

    public double [] addCodeScore(double[] sumCodeScore) {
       double [] modelCodeScore = (double[]) sumCodeScore.clone();

          for(int i = 0; i < rounds+1; i++){
             modelCodeScore [i] += codeScore[i];
          }
          return modelCodeScore;
    }

    public int [] addUniqueAgents(int[]sumUniqueAgents) {
       int [] modelUniqueAgents = (int[]) sumUniqueAgents.clone();

          for(int i = 0; i < rounds+1; i++){
             modelUniqueAgents [i] += uniqueAgents[i];
          }
          return modelUniqueAgents;
    }

    public double [] addMaxScoreHistory(double[]sumMaxScoreHistory) {
       double [] modelMaxScoreHistory = (double[]) sumMaxScoreHistory.clone();

          for(int i = 0; i < rounds+1; i++){
             modelMaxScoreHistory[i] += maxScoreHistory[i];
          }
          return modelMaxScoreHistory;
    }

    public double [] addHeterogeneity(double[]sumHeterogeneity) {
       double [] modelHeterogeneity = (double[]) sumHeterogeneity.clone();

          for(int i = 0; i < rounds+1; i++){
             modelHeterogeneity [i] += heterogeneity[i];
          }
          return modelHeterogeneity;
```

```
    }

    //update models history, to show in chart
    public int getCurrentTick() { return tickCounter; }
    public agent getAgent(int id) { return agentList.get(id); }
    public double[] getAvgScores() { return avgScores; }
    public double[] getAvgScoresRaw() { return avgScoresRaw; }
    public double[] getCodeScores() {return codeScore;}
    public int[] getUniqueAgents() { return uniqueAgents; }
    public double[] getHeterogeneity() {return heterogeneity;}
    public int getRounds() { return rounds; }
    public double[] getmaxScoreHistory() { return maxScoreHistory; }



/************  MAIN FUNCTIONS  *******************/
    //calls each agent in a fixed order and tells it to make a decision
    //depends on the org type and decision strategy of the agents

    //Explore function identical for all strategies
    private void exploreAgents(int clock) {
       switch (strategy_ID) {
       case AGENT:
          for(int i = 0; i < pop; i++) {
             agent a = (agent) agentList.get(i);
             a.explore(clock, space);
          }
          break;
       case INFOM:
          for(int i = 0; i < pop; i++) {
             agent a = (agent) agentList.get(i);
             a.explore(clock, space);
          }
          break;
       case CODE:
          for(int i = 1; i < pop; i++) {
             agent a = (agent) agentList.get(i);
             a.explore(clock, space);
          }
       }
    }

    //for informal models, decision behavior specified by subclasses
    private void learnNeighbor(int clock) {
       for(int i = 0; i < pop; i++) {
          agent a = (agent) agentList.get(i);
          a.neighborlearn(clock);
       }
    }

    //kept seperate to maintain synchronous updating,
    //needed in informal org types
    private void updateAgents(int time) {
       for(int i = 0; i < pop; i++) {
          agent a = (agent) agentList.get(i);
          a.update();
       }
    }

    //for code model
    private void learnCode(int clock) {
       agent_CODE a = (agent_CODE) agentList.get(0);
       a.codelearn(clock);
    }

    //for code model
    private void socialisationAgents(int clock) {
       for(int i = 1; i < pop; i++) {
          agent_CODE a = (agent_CODE) agentList.get(i);
          a.socialisation(clock);
```

```
        }
    }

    //for informal models
    //map each agent's score through rank-preserving function,
    //average them together
    private double avgPopScore() {
       double sum = 0;
          for(int i = 0; i < pop; i++) {
           agent a = (agent) agentList.get(i);
           //calculate adjusted agent score
             sum += Math.pow ((a.getScore()/MAXSCORE), 8);
          }
          return (sum/pop); //return the average
    }

    //for code model
    private double avgPopScoreWoCode() {
       double sum = 0;
          for(int i = 1; i < pop; i++) {
           agent a = (agent) agentList.get(i);
          sum+=a.getScore();
          }
          return (sum/(pop-1)); //return the average
    }

    //for informal models
    //returns the average score
    private double avgPopScoreRaw() {
       double sum = 0;
          for(int i = 0; i < pop; i++) {
           agent a = (agent) agentList.get(i);
              sum +=a.getScore()/MAXSCORE;
          }
          return (sum/pop); //return the average
    }
    //for code model
    private double avgPopScoreRawWoCode() {
       double sum = 0;
          for(int i = 1; i < pop; i++) {
           agent a = (agent) agentList.get(i);
              sum +=a.getScore()/MAXSCORE;
          }
          return (sum/(pop-1)); //return the average
    }

    //return the codeScore/orgScore
    private double codeScore() {
       double orgScore;
       agent a = (agent) agentList.get(0);
    // orgScore = a.getScore()/MAXSCORE; //for stable env
       orgScore = a.getScore(); //for turb env

    return (orgScore);   //return the codeScore
    }

    //returns the amount of agents with a unique score
    public int numUniqueAgents() {
       ArrayList<Double> uniqueList = new ArrayList<Double>();
       for(int i = 0; i < pop; i++) {
          agent a = (agent) agentList.get(i);
          Double Score = new Double(a.getScore());
          if(!uniqueList.contains(Score)) {
             uniqueList.add(Score);
          }
       }
       return uniqueList.size();
    }

    //heterogeneity of agents
```

```
   private double heterogeneityPop() {
      int dis = 0;
      double quot = (pop*(pop-1)*space.getN())/2;

      for (int i = 0; i < pop; i++ ){
         agent a = (agent) agentList.get(i);
         a.getSoln();

            for (int j = i+1; j < pop; j++){
               agent b = (agent) agentList.get(j);
               b.getSoln();

                  for (int k = 0; k < space.getN(); k++){
                     if (a.getSoln()[k] != b.getSoln()[k]){
                        dis++;
                     }
                  }
            }
      }
      return dis/quot;
   }

/******************  DATA GENERATION *******************/

   //save modelruns to text file, save complete run (all ticks)
   //adds following model's data to the end of file
   public void saveSPSSseveral(String filename) throws IOException {
      if (!filename.endsWith(".txt"))
         filename += ".txt";

      new java.io.File(filename).createNewFile();

      RandomAccessFile file = new RandomAccessFile(filename, "rw");


      file.writeChars(getStrategyID()+" agents_"+agentList.size()+"
      ticks_"+rounds+" NW_"+getNetType()+ " Env_"+getEnvironmentVariables()+"
      "+getAgentProbabilities());
      file.writeChars("\n");
      file.writeChars("tick,  learningSuccess,  codeScore,  uniqueSolutions,
      heterogeneity,  avgScores,  maxScore");
      file.writeChars("\n");
      file.seek(file.length());

      file.writeChars(modelID+":");
      file.writeChars(seed+"\n");

      for (int i = 0; i <= rounds; i++) {
         file.writeChars(i+", ");
         file.writeChars (avgScoresRaw[i]+", ");
         file.writeChars(codeScore[i]+", ");
         file.writeChars(uniqueAgents[i]+", ");
         file.writeChars(heterogeneity[i]+", ");
         file.writeChars(avgScores[i]+", ");
         file.writeChars(maxScoreHistory[i]+"");
         file.writeChars("\n");
      }
      file.close();
   }

   //save modelruns to text file;
   //save only last results of last tick
   //adds following model's data to the end of file
   public void saveSPSSseverallastTick(String filename) throws IOException {
      if (!filename.endsWith(".txt"))
         filename += ".txt";

      new java.io.File(filename).createNewFile();

      RandomAccessFile file = new RandomAccessFile(filename, "rw");
```

```
   file.writeChars(getStrategyID()+" agents_"+agentList.size()+"
   ticks_"+rounds+" NW_"+getNetType()+ " Env_"+getEnvironmentVariables()+"
   "+getAgentProbabilities());
   file.writeChars("\n");
   file.writeChars("learningSuccess,  codeScore,  uniqueSolutions,
   heterogeneity,  avgScores,  maxScore");
   file.writeChars("\n");
   file.seek(file.length());

      file.writeChars (avgScoresRaw[299]+", ");
      file.writeChars(codeScore[299]+", ");
      file.writeChars(uniqueAgents[299]+", ");
      file.writeChars(heterogeneity[299]+", ");
      file.writeChars(avgScores[299]+", ");
      file.writeChars(maxScoreHistory[299]+"");
      file.writeChars("\n");

   file.close();
}

//writes this model's parameters to the end of a given file
public void saveParameters(String filename) throws IOException {
   if (!filename.endsWith(".txt"))
      filename += ".txt";

   RandomAccessFile file = new RandomAccessFile(filename, "rw");

   file.seek(file.length());//go to end of file

   file.writeLong(seed);
   file.writeInt(modelID);
   file.writeUTF(space.spaceFile);
   file.writeInt(pop);
   file.writeInt(netType);
   file.writeUTF(flArToStr(netInfo));
   file.writeUTF(dblFlArToStr(agentProbabilities));
   file.writeInt(rounds);
   file.writeInt(x);
   file.writeDouble(t);
   file.writeBoolean(keepDependenciesOnChange);
   file.writeInt(strategy_ID);

   //at last, write a new line &close the file
   file.writeChars("\n");
   file.close();
}

//parses and possibly loads a model's parameters
//by a given seed from a given file
public static model loadParameters(String filename, long seed) throws
IOException {

   RandomAccessFile file = new RandomAccessFile(filename, "r");
   file.seek(0);
   while (file.getFilePointer() != file.length()) {
      try {
         Long val = file.readLong();
         if (val == seed) {
            model res = new model(
                  file.readInt(),
                  file.readUTF(),
                  file.readInt(),
                  file.readInt(),
                  strToFlAr(file.readUTF()),
                  strToDblFlAr(file.readUTF()),
                  file.readInt(),
                  file.readInt(),
                  file.readDouble(),
                  file.readBoolean(),
```

```
                    file.readInt(),
                    seed);
              file.close();
              return res;
           }
           else
              file.readLine();
        } catch (IOException e) {
           file.readLine();
        }
     }
     file.close();
     throw new IOException();
  }

/******************  HELPER FUNCTIONS ********************/

  //takes a network object and maps the matrix form to
  //local agent neighbor ties
  public void assignNeighbors(netObj net) {
     for(int i = 0; i < pop; i++) {
        agent hub = (agent) agentList.get(i);
        for(int j = 0; j < pop; j++) {
           //check to see if a link exists
           if(net.isLink(i, j)) {
              agent link = (agent) agentList.get(j);
              //links are symmetric
              hub.neighbors.add(link);            }
        }
     }
  }

  //serializes a double array
  public static String flArToStr(double[] flAr) {
     String res = "";
     for (int i=0; i<flAr.length; i++) res+=String.valueOf(flAr[i]+",");
     return res;
  }

  //deserializes a double array
  public static double[] strToFlAr(String str) {
     String[] splitted = str.split(",");
     int size = splitted.length;
     double[] res = new double[size];
     for (int i=0; i<size; i++) res[i]=Double.parseDouble(splitted[i]);
     return res;
  }

  //serializes a 2-dim double array
  public static String dblFlArToStr(double[][] dblFlAr) {
     String res = "";
     for (int i=0; i<dblFlAr.length; i++) {
        for (int j=0; j<dblFlAr[i].length; j++)
           res+=String.valueOf(dblFlAr[i][j]+",");
        res += ";";
     }
     return res;
  }

  //deserializes a 2-dim double array
  public static double[][] strToDblFlAr(String str) {
     String[] agents = str.split(";");
     int pop = agents.length;
     double[][] res = new double[pop][(str.split(",").length)/pop];
     for (int i=0; i<pop; i++) {
        String[] vals = agents[i].split(",");
        for (int j=0; j<vals.length; j++)
           res[i][j]=Double.parseDouble(vals[j]);
     }
     return res;
```

```
   }
 }
```

example.java

```
/*
 * The code was originally designed for
 * (Lazer, David and Allan Friedman.
 * "The Network Structure of Exploration and Exploitation."
 * Administrative Science Quarterly, 52:4. 2007)
 * Licensed under Creative Commons Attribution-Share Alike CC(2007),
 * http://creativecommons.org/licenses/by-nc-sa/3.0/us/
 * Changed and adapted by Seidel, Eva. "Path Dependence and the Environmental
 * Context" PhD, Free University of Berlin
 * Specifies settings for experiments.
 * */

public class example {

      public static void main(String[] args) throws Exception {

         int xAxisLabelsToShow = 20;

         //create new landscapes
      /* for (int j = 0; j < 100; j++){
         NK_gen l = new NK_gen(15,10);
         l.build_space();
         l.write_to_file("landscape_15_10_"+j);
         //get number of local maxima
         System.out.println(l.getNumPeaks()+" "+l.getMaxScoreExample());}}*/

         // population
         int pop = 51;

         //modelruns
         int modelruns = 600;

         //Strategy: 1 INFORMAL Tournament, 2 INFORMAL Majority, 3 CODE
         int strategyID = 3;

         //Network: 1 LINE, 2 FULL, 3 RANDOM, 4 SMALLWORLD
         int nettype = 2;

         double[][] agentProbabilities = new double[pop][3];
         for(int i = 0; i < pop; i++) { //agents have default behavior
            agentProbabilities[i][0] = 0.0; //explore
            agentProbabilities[i][1] = 0.1; //AGENTS
            agentProbabilities[i][2] = 0.9; //CODE
         }

         // netstuff allows distributions to be sent to netObj
         double[] netstuff = {10};//re-wiring for small-world

         // the amount of ticks
         int ticks = 300;

         // determines the frequency of landscape changes
         // set -1 for the landscape not to alternate
         int period = 5;

         // determines the negative intensity of those changes
         double tau = 0.2;

         //determines, whether the landscape keeps the dependencies on a change
         boolean keepDependenciesOnChange = true;

         //create and save models
```

```
        double[]sumAvgScores = new double[ticks+1];
        double[]sumAvgScoresRaw = new double[ticks+1];
        double[]sumCodeScore = new double[ticks+1];
        int[]sumUniqueAgents = new int[ticks+1];
        double[]sumHeterogeneity = new double[ticks+1];
        double[]sumMaxScoreHistory = new double[ticks+1];

        for (int i = 0; i < modelruns; i++){
           int modelID = i;

           //landscape file
           String space = "landscape_15_3_"+i+".nk";

           //create model
           model m = new model (modelID, space, pop, nettype, netstuff,
           agentProbabilities, ticks, period, tau, keepDependenciesOnChange,
           strategyID);

           //save model results to text file
           //writes data to end of file
           m.saveSPSSseverallastTick(m.strategy_ID+"_runs_"+ modelruns+
           "_ticks_"+ticks+"_Env_"+ m.getEnvironmentVariables()+"_lT");
           m.saveSPSSseveral(m.strategy_ID+"_runs_"+ modelruns+
           "_ticks_"+ticks+"_Env_"+ m.getEnvironmentVariables());

           // text output of the model results
           m.printEvolution();

           //save model parameters
           //writes data to end of file
           m.saveParameters("seed.txt");

           //save output parameters
           sumAvgScores = m.addAvgScores(sumAvgScores);
           sumAvgScoresRaw = m.addAvgScoresRaw(sumAvgScoresRaw);
           sumCodeScore = m.addCodeScore(sumCodeScore);
           sumUniqueAgents = m.addUniqueAgents(sumUniqueAgents);
           sumHeterogeneity = m.addHeterogeneity(sumHeterogeneity);
           sumMaxScoreHistory = m.addMaxScoreHistory(sumMaxScoreHistory);
        }

        //save data of file
        Chart.saveFileChart("cd.txt", modelruns, pop, nettype, netstuff,
        ticks, period, tau, strategyID, sumAvgScoresRaw, sumCodeScore,
        sumUniqueAgents, sumHeterogeneity, sumAvgScores, sumMaxScoreHistory);

        // graphical output of several models
        Chart.showChartVariousModelsAvgScoresAndUniqueAgents(modelruns, pop,
        nettype, netstuff, ticks, period, tau, strategyID,
        sumAvgScoresRaw, sumCodeScore, sumUniqueAgents, sumHeterogeneity,
        sumAvgScores, sumMaxScoreHistory, xAxisLabelsToShow);

        // save the diagram as file: dia1.svg
        Chart.saveChartVariousModelsAvgScoresAndUniqueAgentsSVG(modelruns,
        pop, nettype, netstuff, ticks, period, tau, strategyID,
        sumAvgScoresRaw, sumCodeScore, sumUniqueAgents, sumHeterogeneity,
        sumAvgScores, sumMaxScoreHistory, xAxisLabelsToShow, "dia_models.svg",
        1600, 800);
        }
}
```

C Number of Local Optima in NK Space

For our moderately complex environment with $N = 15$ we set $K = 3$. One hundred NK spaces with this configuration showed a mean number of local optima of 37.41.

For highly complex environments we set $K = 10$. One hundred NK spaces with this configuration showed a mean number of local optima of 394.54.

D Estimation of Error Variance

probExplore	probCode	probAgents	numBetterPerf	Setting
0,1	0,1	0,1	5	low
0,5	0,5	0,5	5	medium
0,9	0,9	0,9	5	high
0,9	0,1	0,9	5	high/low combination 1
0,9	0,9	0,1	5	high/low combination 2

Table 20: Preliminary design points for the estimation of the error variance

Error Variance Matrix		learning success (# runs)	code score(# runs)
K3 configurations	Runs_Code_K3_low	100	100
	Runs_Code_K3_medium	600	600
	Runs_Code_K3_high	400	400
	Runs_Code_K3_combi1	400	400
K10 configurations	Runs_Code_K10_low	300	300
	Runs_Code_K10_medium	< 200	< 200
	Runs_Code_K10_high	< 200	< 200
	Runs_Code_K10_combi1	500	500
	Runs_Code_K10_combi2	300	300

Table 21: Results of the estimation of error variance for the described design points[277]

The $numBetterPerf$ is set to 5 as in the experiments conducted with the model. For defining learning by the code in a similar way as March (1991), we experienced oscillating behavior of the model. Behavior of this kind requires much higher amounts

277 Table 21 displays the number of runs after which a further increase of the number of runs did not alter the coeffcient of variance for the concerned output parameters.

of model runs before stability of the coefficient of variance can be provided. The the variance of the output variables does not stabilize for an affordable number of runs which is a common problem in simulation research where defining the number of model iterations is often a trade-off between stability and costs (Lorscheid, Heine, & Meyer, 2011: 13). As our target when working with the original March configuration when individual learning is involved[278] consist mainly in showing a specific behavior and not so much in comparing the output variables of different settings, we similarly settle for this configuration with 600 runs.

E Required Number of Ticks

Number of ticks		
NK	design point	ticks
15_10	medium	learning success stable at least after 50 ticks
15_3	medium	learning success stable at least after 35 ticks
NK		
15_10	low	learning success stable at least after 400 ticks
15_3	low	learning success stable at least after 250 ticks
NK		
15_10	high	learning success stable after 1 tick
15_3	high	learning success stable after 1 tick

Table 22: Assessment of the number of required ticks for the model with a stable environment

F Simulation Output

Each simulation experiment generates output in three text files as well as an svg graphic file showing the aggregated simulation history of all dependent variables averaged over the specified number of runs. Two text files store the simulation history. One text file provides the results for the dependent variables, for every tick of each run. Another text file shows results aggregated over all runs, for every dependent

[278] See Figure 30 in chapter 6.3.3.2.

variable for every tick averaged over the specified number of runs. Moreover, the seed values for all runs conducted in a specific experiment are recorded.

G Intensification and Diversification of the Search Process

In a learning model which incorporates individual learning and in which the code learns according to the original logic employed by March (1991), the organization in complex environments experiences fluctuating behavior. According to March (1991), the code accesses all individuals that perform better than the code itself. For all dimensions that the code differs from the majority view, the probability that the code stays unchanged on a specific dimension is $(1 - p_2)^k$ in which k is the number of individuals who differ from the code on this dimension minus the ones who do not. Parameter p_2 is the rate of learning by the code (March, 1991:74).

The fluctuating behavior only occurs in complex environments and it is directly connected to an interaction between the two processes of individual exploration and learning by the code. This is exemplified by the following results. In beneficial learning conditions, the oscillations get stronger with increasing complexity. In detrimental learning conditions, the organization quickly reduces its diversity of beliefs which counteracts strong oscillating tendencies. Here, in regimes of low individual exploration ($p_{expl} = 0.1$, see Figure 30 in chapter 6.3.3.2), no oscillations occur. In regimes of high individual exploration ($p_{expl} = 0.9$, see Figure 48), the organization only oscillates around a very low number of different beliefs.

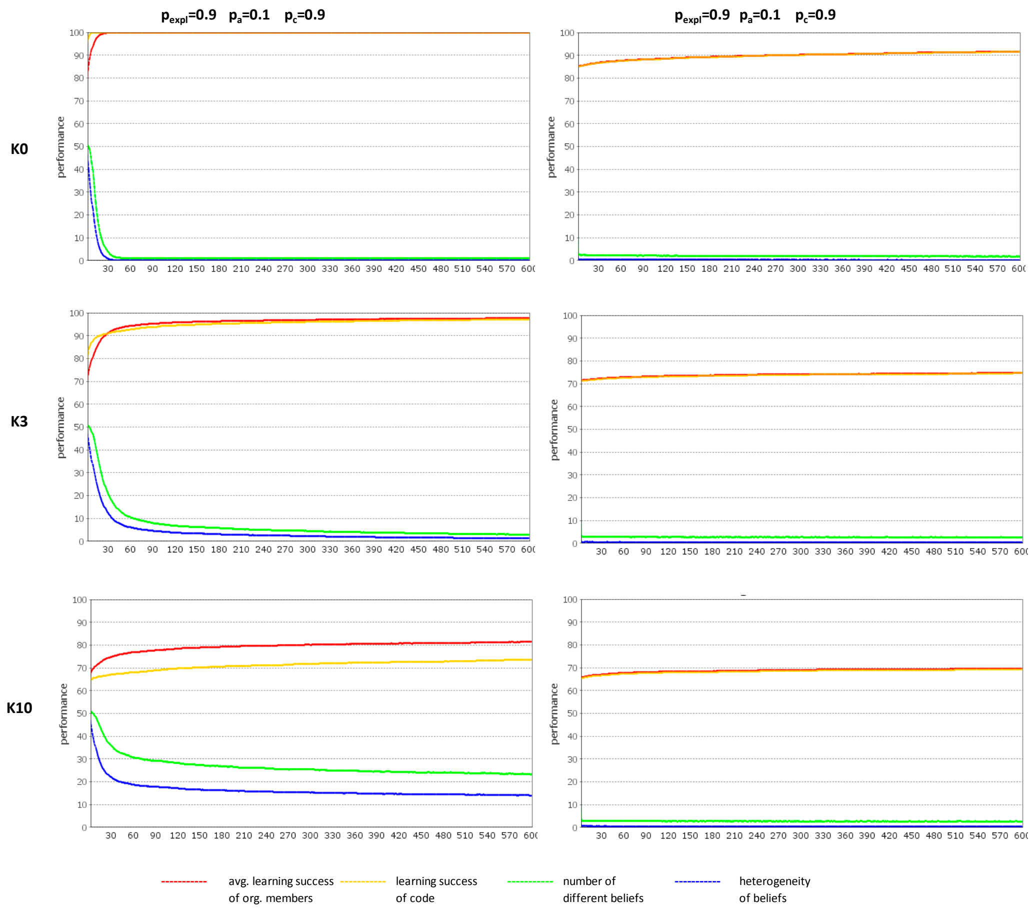

Figure 48: Beneficial and detrimental learning regimes (March logic) in differently complex environments

We also explored other logics for learning conducted by the code which either do not weight dimensional values according to their frequency or employ other procedures to determine which agents are selected into the group of the better performers, e.g. by comparing individual performance with the average performance in the organization.[279] The weighting of beliefs according to the number of better performers who configure the specific belief as does the code, seems to increase the oscillating tendency but oscillating was also recognizable with the other described logics. Further investigation into single model runs tracing the behavior of individual agents and the code showed that the behavior most of all is a result of the interaction between the size of the better performing group and its belief heterogeneity which often makes the code

279 We draw these logics from other studies of organizational learning, see Fang, Lee, & Schilling (2010), Rodan (2005).

unable to identify better solutions. Hence, learning success in the case of oscillating behavior stays low as the organization is unable to reap the benefits from the exploration of the individuals at least in due time.[280]

By setting a parameter which specifies the size of the better performing group ($numBetterPerf$), we further explored this behavior. We investigated organizational behavior for the different elite sizes of 1, 5, and 20 individuals. As could be expected, focusing the code on the one best performer in the organization strongly intensifies the learning process whereas giving the code a large elite ($numBetterPerf = 20$) to learn from leads to more diversification in learning. To assess organizational performance, we compared mutual learning models with different elite sizes for all learning regimes. The results are shown in Figure 49. The impact of the different elite sizes on the history of the learning process, especially the time it takes the organization to converge on one solution, is shown in Figure 50.

In Figure 49, the comparison of the original logic having a flexible elite size with the fixed size approaches shows that a larger elite ($numBetterPerf = 20$), in general, does not improve the learning success of the organization. Moreover, it reduces the differences between the code learning regimes ($p_c = 0.1$; 0.5; 0.9) especially as complexity increases. With a large elite, also the differences between the rates for learning from the code (p_a) are less pronounced. From Figure 50, we derive that while a larger elite does not improve the learning success of the organization, it prolongs the variety of beliefs in the organization. Here, a good solution might get lost in the variety of beliefs of the large elite as the organization is distracted by other solutions. Too large an elite, at last, stops the code from identifying the best solutions and negatively affects learning.

[280] Longer simulation runs (up to 30.000 ticks) showed that the oscillating often seemed to continue indefinitely.

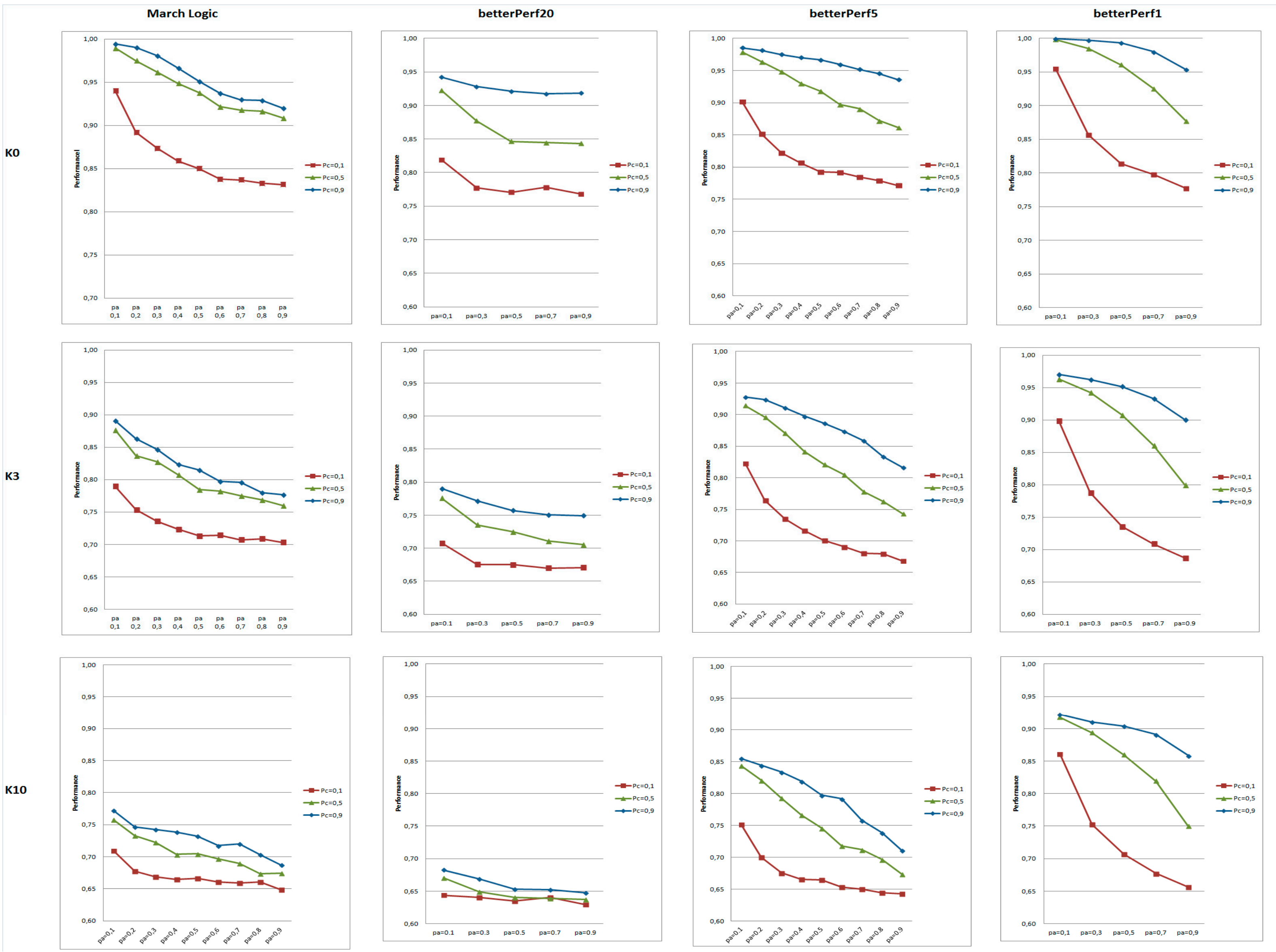

Figure 49: Comparison of the learning regimes with different parameter settings of numBetterPerf (20; 5; 1) and March logic

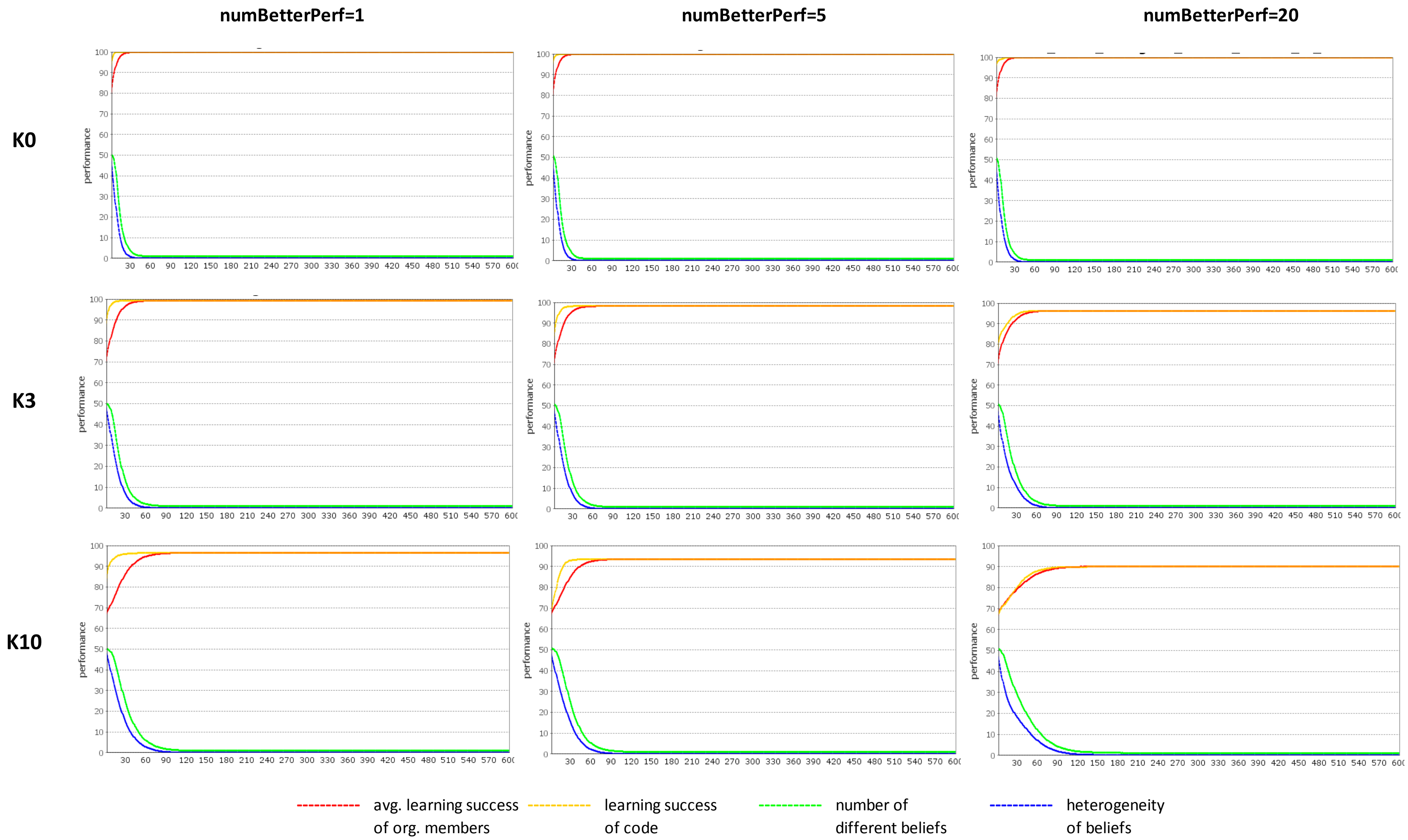

Figure 50: Comparison of the system behavior with different parameter settings of numbBetterPerf in beneficial learning conditions (p_{expl}=0.9; p_a=0.1; p_c=0.9)

H Reporting of Organizational Learning Success: Effect of Environmental Turbulence

In the literature, two different approaches concerning the reporting of performance values in NK landscape models can be found (Ethiraj & Levinthal, 2004; Ganco & Agarwal, 2008; Rivkin & Siggelkow, 2003). Whereas reporting performance values which are normalized to the global maximum in the NK landscape enable us to assess how far from the global optimum the organization got stuck, in a turbulent environment, normalized values are subject to a specific problem. Since past and future performance contributions of the dimensions in the NK landscape (except in extreme cases, where $\tau = 0.0$) are related, the global optimum experiences a regression to the mean. As a result, the organizational performance seems to improve where it actually does not. A visual example for this process is given in the following figure.

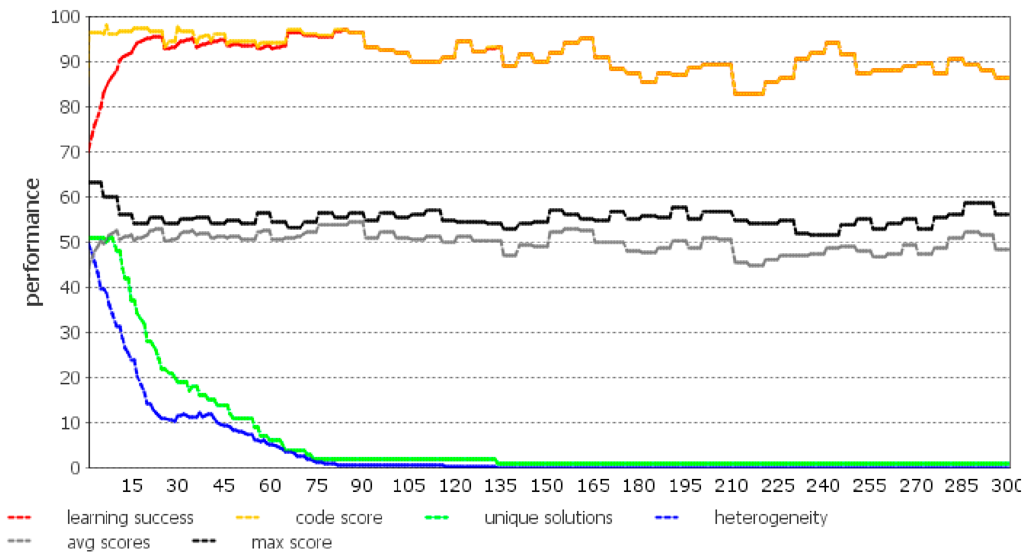

Figure 51: Mutual learning in a simple environment with turbulence (τ=0.8; x=5), example run

From Figure 51, we derive that the maximum score in the NK landscape changes every 5 ticks as this is the specified frequency of environmental change (black curve). The grey curve shows the absolute values of the average learning success in the organization. As usual, the red curve shows the average learning success normalized to the maximum score in the NK landscape. In the beginning, the maximum score (black curve) experiences a decline due to mostly being combined with lower values as a result of environmental change. The normalized learning success (red curve) reflects this decline of the maximum score as a sharp increase since the absolute values of the learning success are divided by declining values of the maximum score. This effect makes it difficult for the researcher to assess the real learning dynamics. For our model in turbulent settings, we decided therefore to report absolute performance values when we aim at assessing the learning history.

Reporting the absolute performance scores also implies that we have to differentiate between regimes of different complexity. The distribution of performance values in landscapes of similar dimensionality but different complexity differs. Due to the increasing interaction effects in more complex landscapes more performance values are drawn for the different bit combinations. In more complex environments, therefore the possibility to have higher maximum scores increases. As a consequence, absolute performance values must only be compared for regimes of similar complexity.

We are mainly interested in the evolving learning dynamics when inquiring into the effects of environmental turbulence and therefore keep environmental complexity stable at a moderate value. Still, to grab the general connection between complexity and turbulence, we ran a comparison of the specified turbulence settings in different complexities ($K = 0; 3; 10$). To be able to compare organizational performance between regimes of different complexities in a similar setting of environmental turbulence, we employ an approach similar to Siggelkow & Rivkin (2005:119). For this purpose, they refer to the average normalized learning success over all periods of the conducted simulation. Table 11 in chapter 6.4.3.1 shows a similar comparison for the parameters of interest in our model.

I Abstract

This dissertation examines the effects of the environmental context on path dependence in organizational learning. We set forth a theoretical framework which explains the path-dependent properties of organizational learning as residing in processes of social adaptation and the competence-enhancing learning of the organizational members. We transform our theoretical framework into an agent-based computer simulation model which combines March's (1991) mutual learning approach and local search processes in an NK landscape. We inquire into the effects of environmental complexity and turbulence on the interplay between the self-reinforcing dynamics of mutual and individual learning. The results emphasize the importance of contextual conditions for the unfolding of organizational path dependence and demonstrate that the effects of the context depend strongly on the prevalent dynamic in the system.

Diese Dissertation befasst sich mit dem Einfluss der Organisationsumwelt auf die Ausbildung von organisatorischen Pfaden. Zunächst wird ein theoretischer Bezugsrahmen entwickelt, der die pfadabhängigen Eigenschaften im organisatorischen Lernen erläutert und in den zwei Lernprozessen, dem kollektivem Lernen basierend auf sozialer Anpassung sowie dem individuellen Kompetenz verstärkendem Lernen verankert. Dieser theoretische Bezugsrahmen wird in ein agentenbasiertes Computersimulationsmodell umgesetzt, das Marchs (1991) Ansatz des „mutual learning" und inkrementelle Suchprozesse in einer NK Fitness Landschaft kombiniert. Auf Basis dieses Modells werden die Effekte von Komplexität und Dynamik der Organsiationsumwelt auf das Zusammenspiel der modellierten Lerndynamiken untersucht. Die Ergebnisse heben die Bedeutung der Umweltbedingungen für die Ausbildung von Pfaden in Organisationen hervor und zeigen auf, dass die kontextualen Effekte stark von der im organisationalen System vorherrschenden Dynamik abhängen.

J Resume Eva C. Seidel

The resume is not included in the online version of the dissertation.