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The Co-Evolution of Technology and Organization

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Dedicated to my parents

Preface

Imagine that you are a captain on a ship. Your mission is to discover new territory. You head to sea with the journals and maps constructed by others who have gone before you. You study these in great detail, combine their insights and techniques, and head for a hitherto unknown destination and destiny. On this journey, you enjoy the freedom and absorb the beautiful scenery that you encounter. However, on occasions, the sea is extremely rough, and storms and thunders threaten to sink your ship and, at times, you even doubt whether you will make it back at all. After much hard work, you encounter a stretch of land that you believe to be undiscovered. You map this new terrain in great detail, in much the same way as others have done before you. Even though you would like to spend more time studying this new land and exploring the ways in which it could be used, you are running low on provisions and need to head back home. On your way back you are obsessively working on completing your journal until, finally, your homeport is in sight. You decide to report your discovery immediately the second that you touch shore. However, when you hit land doubt suddenly enters your mind. What if someone else has already discovered the same land before you? Or, what if the land has no economic use whatsoever? You recollect your adventures and become aware of how much you have learned and realize that the significance of your journey is not dependent upon the economic value of your discoveries. You have grown in many aspects, and you decide then and there that that will be the only measure with which you will judge the significance of your endeavor.

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On a more personal account, I want to thank my parents and my friends Boudewijn, Michiel, Leon, Sven, Koen, Remko, François, Philippe, Ying, Elise, and my brother Hein. Finally, there are two persons who have a special role in my life. First, Bonnie, as you already know, you are my soul mate and you have really changed my life, and I could not have asked for a better friend. And, last but not least, I want to thank Lorraine for putting me under her magical spell.

Table of contents

Preface v
Acknowledgements vii
Table of contents ix
List of figures xi
List of tables xiii
Part I Introduction 15
Chapter 1 Introduction 17
1.1 Introduction 17
1.2 Technology and organization 20
1.3 Evolutionary economics 20
1.4 Organizational ecology 23
1.5 Research objective 26
1.6 Research questions 26
1.7 Organization of this dissertation 31
Chapter 2 Biotechnology 33
2.1 Introduction 33
2.2 What is biotechnology? 33
2.3 The importance of biotechnology 38
2.4 The position of biotechnology in the technological landscape 45
2.5 The future of biotechnology 50
Part II Technology 57
Chapter 3 The Ecology of Technology 59
3.1 Introduction 59
3.2 Endogenous technological growth 61
3.3 The technological niche 62
3.4 Methodology 71
3.5 Results 80
3.6 Discussion and conclusion 87
Chapter 4 The Evolution of Technology 91
4.1 Introduction 91
4.2 Evolution of technology 93
4.3 Stages of technological development 95
4.4 Technological diversity 101
4.5 Data and methodology 104
4.6 Results 113
4.7 Discussion and conclusion 125
Part III Organization 131
Chapter 5 A Logical Formalization of the Theory of the Technological Niche 133
5.1 Introduction 133
5.2 Logical formalization 134
5.3 Non-monotonic logic 137

5.4 Formalizing the theory of the technological niche 140
5.5 Discussion and conclusion 154
Chapter 6 A Logical Extension of the Theory of the Technological Niche 157
6.1 Introduction 157
6.2 Modeling the Evolution of Technology 158
6.3 Crowding revisited 161
6.4 Status revisited 171
6.5 Technological diversity 177
6.6 Technological opportunities 183
6.7 Organizational performance 185
6.8 Discussion and conclusion 186
Chapter 7 An Empirical Test of the Extended Theory of the Technological Niche 191
7.1 Introduction 191
7.2 The Technological Niche and Organizational Innovation 192
7.3 Data and methodology 197
7.4 Estimation 204
7.5 Results 206
7.6 Discussion and conclusion 210
Part IV Conclusion 215
Chapter 8 Conclusion 217
8.1 Introduction 217
8.2 Contribution of this dissertation 217
8.3 Limitations and further research 219
8.4 Broader reflections on the evolution of biotechnology 227
Appendices 233
Appendix A Technological categories and domains 235
Appendix B Descriptive statistics technological domains 237
Appendix C Methodology for argument extraction 245
Appendix D Argumentation patterns 247
Appendix E Background assumptions 249
Appendix F Formal proof theorems Chapter 5 251
Appendix G Logical symbols, predicates, and functions 255
Appendix H Theorem development crowding argument 257
Appendix I Theorem development status argument 259
Appendix J Formal proof theorems Chapter 6 261
Appendix K Regression estimates 279
References 281
Summary 303
About the author 309

List of figures

Figure 1.1 Five-year moving average of the relative number of articles on the topic of innovation and technology in several top-tier executive management journals 19
Figure 1.2 Five-year moving average of the relative number of articles on the topic of innovation and technology in several top-tier academic management and organization journals 19
Figure 1.3 Invention as a process of recombination of (antecedent) components 21
Figure 1.4 The technological lineage of an invention 21
Figure 2.1 The double helix structure of DNA 35
Figure 2.2 Protein synthesis 36
Figure 2.3 Market capitalization 39
Figure 2.4 Relative increase in biotechnology's market capitalization and the NASDAQ composite index 40
Figure 2.5 Biotechnology investments 40
Figure 2.6 Biotechnology products on the US market 41
Figure 2.7 The evolution of biotechnology and biopharmaceutical alliances 42
Figure 2.8 Number of M&As 42
Figure 2.9 Number of biotechnology hits at Google.com per year 43
Figure 2.10 The number of scientific publications on biotechnology per year 44
Figure 2.11 The total number of USPTO Biotechnology and Drugs patents per year 44
Figure 2.12 The number of USPTO Biotechnology and Drugs patents per year relative to the total number of USPTO patents 45
Figure 2.13 Plot of the core of the technological landscape of 1976-1980 47
Figure 2.14 Plot of the core of the technological landscape of 1981-1985 48
Figure 2.15 Plot of the core of the technological landscape of 1986-1990 48
Figure 2.16 Plot of the core of the technological landscape of 1991-1995 49
Figure 2.17 Plot of the core of the technological landscape of 1996-2000 49
Figure 2.18 Plot of the core of the technological landscape of 2001-2005 50
Figure 2.19 An abstraction hierarchy that supports the engineering of integrated genetic systems 54
Figure 3.1 A multi-level model of technology 62
Figure 3.2 The flow of technology and status in technological development 68
Figure 3.3 Local versus global crowding 70
Figure 3.4 Interaction component status and local crowding 86
Figure 3.5 Interaction component status and global crowding 87
Figure 4.1 A technological system composed of components, subcomponents, and inventions ..95
Figure 4.2 Characteristics of the different stages of technological development 96
Figure 4.3 The organization's strategy and stages of technological development 129
Figure 5.1 Original and new argumentative structure of the crowding theorem 142
Figure 5.2 Structure of technological crowing argument 147
Figure 0.3 Structure of technological status argument 153

Figure 6.1 Stage-dependent uncertainty 160
Figure 6.2 Argumentative structure crowding 171
Figure 6.3 Argumentative structure status 177
Figure 6.4 Argumentative structure diversity 183
Figure 6.5 Argumentative structure technological opportunities 185
Figure 6.6 Alternative effects of system changes 187
Figure 8.1 Hierarchical model of technology 222
Figure 8.2 The organization's strategy and stages of technological development 223
Figure 8.3 A hierarchical co-evolutionary model of technology and organization 224
Figure 8.4 Stable technological configurations at multiple levels of our hierarchical co-evolutionary model 225
Figure 8.5 Synthetic biology 229

List of tables

Table 3.1 Biotechnology's technological component niches....72
Table 3.2 Descriptive statistics of patent entry into biotechnology's components....75
Table 3.3 Definition of variables....76
Table 3.4 Summary statistics....76
Table 3.5 Correlation matrix....77
Table 3.6 Alternative specifications for organizational, component, and system....81
Table 3.7 Negative binomial random effects panel regression estimates of alternative density specifications....83
Table 3.8 Negative binomial random effects panel regression estimates of full model....84
Table 3.9 Overview of our hypotheses and findings....88
Table 4.1 Definition of variables....106
Table 4.2 Descriptive statistics....107
Table 4.3 Correlation matrix....107
Table 4.4 Stages of technological evolution and threshold values of the cumulative density function....108
Table 4.5 Negative binomial regression estimates of Bass model for biotechnology's components....114
Table 4.6 Threshold values different stages of technological evolution according to estimates from the negative binomial Bass model....115
Table 4.7 Negative binomial regression estimates of multi-level structural break model of biotechnology's components....116
Table 4.8 Start date of growth stage according to different models....118
Table 4.9 Negative binomial dynamic panel regression estimates of alternative structural break models....120
Table 4.10 Confidence interval for entry and growth in different stages of technological development....121
Table 4.11 Negative binomial dynamic multi-level panel regression estimates of the seed stage of technological evolution....122
Table 4.12 Negative binomial dynamic multi-level panel regression estimates of the growth stage of technological evolution....123
Table 4.13 Overview of hypotheses and results....126
Table 5.1 Glossary of symbols....139
Table 6.1 The effect of technological crowding and non-crowding in different stages of technological development....165
Table 7.1 Summary statistics....202
Table 7.2 Correlation matrix....203
Table 7.3 Number of organizations and observations from different regions used in our analyses....207
Table 7.4 Restricted negative binomial panel regression estimates....209

Table 7.5 Signs and significance levels of coefficient estimates under alternative specifications 211
Table 8.1 A hypothetical technological system with five component technologies 218
Table 8.2 Systemic changes 226
Table A.1 Technological categories and domains 235
Table B.1 Status rank of technological domains 238
Table B.2 Status of technological domain 239
Table B.03 Growth rate of patents in percentages of previous period 240
Table B.4 Number of patents in technological domains in different periods 241
Table B.5 Percentage of patents in technological domains in different periods 242
Table B.6 Ranking on the basis of share of total patents per period 243
Table G.1 Logical symbols, predicates, and functions 255
Table H.1 Partial modified truth table of crowding argument.. 257
Table H.2 Legend 257
Table I.1 Partial modified truth table of status argument 259
Table I.2 Legend 259
Table K.1 Restricted negative binomial panel regression estimates 279
Table K.2 Unrestricted negative binomial panel regression estimates 280

Part I Introduction

"The formulation of a problem is often more essential than its solution."

~ *Einstein*

Chapter 1

Introduction

1.1 Introduction

Technology is becoming increasingly important for policy-makers. For example, EU policy-makers attribute a highly important role to technology and innovation to transition the 'old' EU into a 'new' knowledge-based EU, as can be seen in Box 1.1. Moreover, in response to the global economic crisis, one of the main goals of the American Recovery and Reinvestment Act of 2009 is to "provide investments needed to increase economic efficiency by spurring technological advances in science and health" (American Recovery and Reinvestment Act, 2009: H.R.1–2).

The Importance of Innovation in the EU

In the beginning of this century, the European Council set out an action and development plan, labeled the Lisbon Strategy, with the aim to make the EU the most competitive economy in the world by investing in the transition of the 'old' EU to a 'new' competitive, dynamic and knowledge-based economy. After all, the EU performs weakly in comparison with its major competitors (i.e., USA and Japan) on numerous performance indicators, especially those related to knowledge and innovation. As such, one of the priority areas outlined in the Lisbon strategy is investing more in knowledge and innovation.

Even though the EU has made considerable progress over the last years, many experts claim that the EU still has a long way to go, and needs to boost innovation for both social and economic reasons. According to these experts, the 'innovation gap' reflects, amongst others, a weakness in the links between research and industry. The European Council has, therefore, adopted integrated guidelines that form the basis for member states' national reform programs and channel their efforts towards key priority areas. One of these guidelines (guideline No 8) is to facilitate all forms of innovation, see below.

Guideline No 8

To facilitate all forms of innovation, Member States should focus on (European Union, 2008):

- Improvements in innovation support services, in particular for dissemination and technology transfer;
- The creation and development of innovation poles, networks and incubators bringing together universities, research institutions and enterprises, including at regional and local level, helping to bridge the technology gap between regions;
- The encouragement of cross-border knowledge transfer, including from foreign direct

investment;

- Encouraging public procurement of innovative products and services;
- Better access to domestic and international finance;
- Efficient and affordable means to enforce intellectual property rights.

As argued above, the transition of the EU to a competitive, dynamic, and knowledge-based society is dependent on the EU's innovative capacity. In this respect, biotechnology is a key priority area, which is reflected in the fact that the European Commission has put the biotech industry firmly on the map when it reformulated a strategy for Europe on Life Sciences and Biotechnology in 2002, aimed at promoting a sustainable bio-economy. The reason for doing so is that biotechnologies are believed to play a vital role in the future of human kind. After all, even though biotechnologies have been around for over 5,000 years (e.g., in the making of bread, cheese, beer, and wine), current developments offers prospects of sustainable energy sources and major breakthroughs in the field of medicine (BIO, 2006).

Box 1.1 The importance of innovation in the European Union

The management of technology and innovation is also becoming increasingly important for CEOs. Consider, for example, the increase in the relative number of articles in some of the leading journals for management executives (i.e., *California Management Review*, *Academy of Management Executive*, *MIT Sloan Management Review*, and *Harvard Business Review*) on the topic of innovation and technology, as visualized in Figure 1.1. In the academic domain, we can notice a similar increase in focus on the subject of technology and innovation. While technology and innovation received little attention in the top-tier management and organization journals (i.e., *Administrative Science Quarterly, Academy of Management Review, Academy of Management Journal, Organization Science,* and *Strategic Management Journal*) in the 80's, we can observe a steady increase in the relative number of publications on the topic of technology and innovation since 1990.

Despite the recent increase in attention to technology and innovation, the importance of technology and innovation, however, is not a contemporary observation. Schumpeter (1934) already posited technology as the driving force behind economic development many decades ago. Since then, many scientists acknowledge the importance of technology in the evolution of our society (Anderson & Tushman, 1990; Dosi, 1982; Lawless & Anderson, 1996; Nelson & Winter, 1982). However, despite this awareness within the scientific community, technology or technological change is a phenomenon that is not well understood. By means of this dissertation, we therefore hope to contribute to furthering our understanding of technology and technological change. Because, nowadays, technology is developed more and more in an organizational context, we do this by studying technology in the context of organization science, which is an academic discipline that studies all facets of organization.

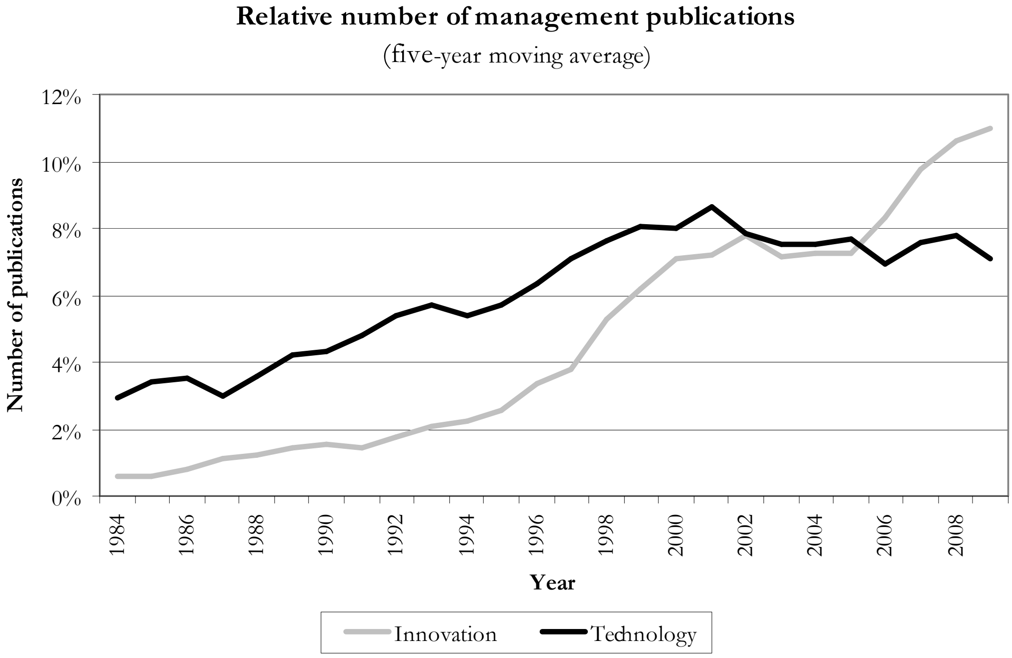

Figure 1.1 Five-year moving average of the relative number of articles on the topic of innovation and technology in several top-tier executive management journals

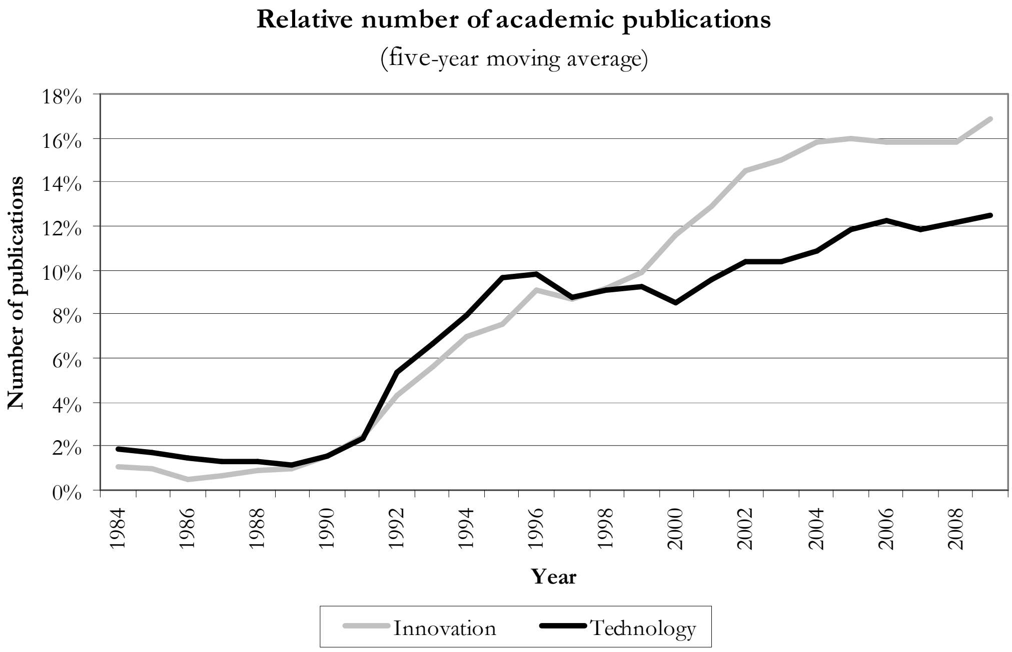

Figure 1.2 Five-year moving average of the relative number of articles on the topic of innovation and technology in several top-tier academic management and organization journals

The organization of this chapter is as follows. In the next section, we will briefly discus the standing of technology in the context of organization science. Then, in Section 1.3, we briefly introduce the field that is associated most with the study of technology in an organizational context: evolutionary economics. Section 1.4 subsequently discusses the core logic of a domain that we believe can contribute significantly to our understanding of technology: organizational ecology. Section 1.5 introduces the research objective of this dissertation. Section 1.6 presents the research questions that we derive from this objective. Finally, Section 1.7 gives a short overview of the organization of this dissertation.

1.2 Technology and organization

Even though quite a few pioneer economists in the neoclassical tradition did recognize the role of technical change, they have generally assumed technological progress to be a mere shift along the production function. From this perspective, technological change is considered to be an exogenous variable. The process of technological growth thus remains a 'black box' or, in Solow's famous formulation, technological progress's outcomes appear as noise in the residual of a regression equation (Rosenberg, 1982). Following Marx (1906), Schumpeter (1943), who is considered by many as the founding father of modern innovation theory, presented an evolutionary theory on the working of the capitalist system, driven by forces of technological change. Since then, many scholars have emphasized the importance of technology in shaping economic processes. By now, to argue that technology is a powerful force (Lawless & Anderson, 1996) that drives a variety of economic phenomena (Nelson & Winter, 1982) is stating the obvious. It is for this reason that Tushman and Nelson (1990) already concluded almost two decades ago that technology deserves a central role in any organization theory. However, despite this call for a systematic study of technology in an organizational context, progress has been rather haphazard. Only within evolutionary economics does technology have a central role, even though technology does receive some attention within organizational ecology and industrial organization. So, technology has not yet penetrated fully the domain of organization science, resulting in the fact that the process of technological change is not yet fully understood. In this dissertation, therefore, we want to demonstrate that, by studying technology from an ecological perspective (i.e., organizational ecology), we can add insights above and beyond the ones that originate from evolutionary economics alone. In doing so, we not only contribute to our understanding of the process of technological change, but also close part of the chasm that exists in the debate between organizational adaptation and environmental selection schools of thought (Baum, 1996; Lewin & Volberda, 1999; van Witteloostuijn, 1994).

1.3 Evolutionary economics

At the heart of evolutionary economics lies the notion of endogenous technological change as a process of recombination (Fleming, 2001), where (existing) components are brought together in new ways (Schumpeter, 1939). This conception of technological change as a process of recombination has been widely adopted in the literature. In this dissertation, we follow this tradition, and view technological change (i.e., invention) as a process of recombination of components, where components refer to the constituents of invention (Fleming, 2001). Characterizing technological change as a process of recombination implies technological lineage, where an invention builds upon antecedent inventions (see Figure 1.3), and can subsequently becomes the basis for future (descendant) inventions itself. This logic is demonstrated in Figure 1.4.

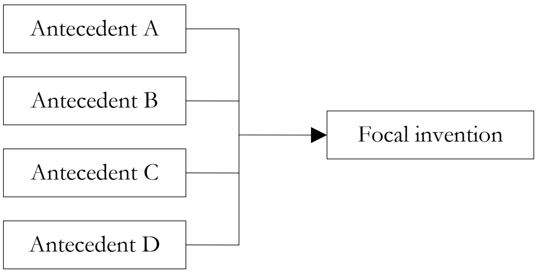

Figure 1.3 Invention as a process of recombination of (antecedent) components

In this evolutionary logic of technological change, diversity (i.e., the heterogeneity of components) forms a central notion. The reason is that diversity forms the input to the process of recombination, and it is therefore considered to be the ultimate source of novelty (Johnson, 1992; Nooteboom, 2000). However, because any component can be combined with every other component, the number of potential combinations increases exponentially with the number of components. Hence, the complete set of potential combinations quickly becomes incomprehensible, and an inventor (or a population of inventors; e.g., an organization) can only consider a limited number of components and combinations simultaneously (Fleming, 2001). This observation is also known as the bounded rationality assumption, which also lies at the heart of evolutionary economics. As a result, individuals, organizations, and communities[1] are argued to search and recombine locally from and among a limited set of components (Fleming, 2001).

Figure 1.4 The technological lineage of an invention

At the organizational level, this translates into organizational routines that enable regular and predictable patterns of behavior (Nelson & Winter, 1982). At the level of a technological community, this implies regular and predictable patterns of technological growth (Dosi, 1988; Foster, 1986; Nelson & Winter, 1982). These stable and predictable

[1] Here, community refers to the members of a technological domain (e.g., biotechnology or semiconductor technology).

patterns of technological growth go by many different names such as, amongst others, natural trajectories (Nelson & Winter, 1982), technological regimes (Winter, 1984), dominant designs (Utterback & Abbernathy, 1975), technological paradigms (Dosi, 1982), technological guideposts (Rosenberg, 1976), and design hierarchies (Clark, 1985). These stable and predictable patterns of technological growth result from the stable configuration of the set of technological components that belong to a particular technological system or community. As such, this stable configuration identifies the major components to be developed, as well as the relationships among these components. This facilitates cumulative growth as "research becomes increasingly specialized and sophisticated and the technology is broken down into its component parts with individual investigations focusing on improvements in small elements of the technology" (Mueller & Tilton, 1969: 576). These stable configurations thus enable specialization and subsequent integration of the specialized components, implying that (groups of) individuals and organizations no longer have to invest in learning many alternative configurations, but can concentrate their (limited) learning resources largely on (a part of) the technology's dominant design configuration (Henderson & Clark, 1990).

Clearly, these stable configurations or structures do not emerge *ex nihilo*, but have to be created somehow by the stakeholders of the particular technology. This logically implies the existence of different stages of technological development. First, there is a stage in which the stable configuration is socially constructed by the stakeholders in the environment. Because this stage is characterized by the existence of diverging viewpoints regarding the configuration of technology, we refer to this stage as the stage of divergence. Second, the creation of a stable configuration implies a consensus among the technology's stakeholders regarding the configuration of technology. As such, in this stage, developments converge towards the collectively-agreed-upon design configuration of the technology's components, implying technological determinism. We label this the stage of convergence. The distinction between the stages of divergence and convergence is is similar to, for instance, Anderson and Tushman's (1990) era of ferment and incremental change (or order), Utterback and Abernathy's (1975) fluid and specific technological change, or Dosi's (1982) paradigmatic and pre-paradigmatic stages of technological development, respectively. The stages also connect to the more general life cycle theory. More specifically, the divergence stage of social construction can be characterized by the seed stage in life cycle theory, while the convergence stage of technological determinism can be characterized by the growth stage in life cycle theory.

Bascially, the different stages of technological development refer to the different characteristics of the selection environment. A much debated and important characteristic of this environment is the level of uncertainty (Dosi, 1982; Fleming, 2001; Nelson & Winter, 1982; Podolny, Stuart, & Hannan, 1996; Rosenberg, 1996). On the one hand, in the stage of technological divergence, uncertainty is relatively high as the scientific and technological principles on which technological growth should be based are yet unknown (Dosi, 1988). On the other hand, during the stage of technological convergence, the stable configuration contains strong prescriptions on which directions of technological change to pursue and which to neglect (Dosi, 1982; Rosenberg, 1982), which significantly reduces the level of uncertainty. This is similar to Knight's (1921) distinction between uncertainty (i.e., unknown unknowns) and risk (i.e., known unknowns).

To date, the evolutionary economics literature is biased to the study of technological diffusion (Stuart, 1999), implying that the level and nature of technological variety are exogenous to the theory. Indeed, evolutionary economics has been successful in analyzing processes of technological diffusion, but much less is known about the very nature and origin of variety that drives technological growth. In this respect, we believe that organizational ecology can contribute, being evolutionary economics' counterpart in sociology, both sharing an emphasis on the ecological variation-selection-retention logic. Much organizational ecology focuses on the influence of environmental features on organizational entry and exit, seeking answers to the question "Why are there so many different kinds of organizations?" (Hannan & Freeman, 1977). So, organizational ecology considers the effect of the (structural) characteristics of the (selection) environment on evolutionary processes (growth; the entry and exit of variety) within organizational populations. The argument here is that a similar logic can be effectively applied to technological populations.

1.4 Organizational ecology

Like evolutionary economics, organizational ecology was introduced in the mid-1970s. Hannan and Freeman (1977) developed a response to the then contemporary organizational theories that emphasized the flexibility and adaptability of organizations surviving in changing environments. In contrast to the dominant assumption in organization theory and strategic management that organizations are rapid and flexible adapters, organizational ecology stresses that, due to the requirements of reliability and predictability, organizations are inert and core changes pose a severe threat to the survival chances of organizations. As a result, organizational ecology argues that most of the variation in organization populations comes about by the creation of new organizational forms and the demise of their old counterparts, whereas only a small part of population-level change is the result of adaptation of organizations. Hence, selection is assumed to be the dominant force. However, this does not mean that organizational ecologists assume that organizations cannot adapt. On the contrary, the argument of organizational ecology centers on the fact that due to the success of the organization in adapting to its past circumstances, the organization is hindered from adapting to changing or different circumstances (i.e., path dependence). More specifically, because the organization's (internal and external) stakeholders have formed clear expectations about the identity of the organization, radically changing the organization's triggers a legitimation crisis, as the stakeholders have to adapt their expectations. So, organizational ecology redirected attention to the population level of analysis, emphasizing environmental selection and de-emphasizing organizational adaptability. Hence, the origin of organizational variety is argued to be located in entry and exit processes, rather than in adaptation of individual organizations. From this core logic, organizational ecology has developed fine-grained theory and has collected much evidence as to the evolutionary processes of and within organizational populations (Carroll & Hannan, 2000).

Theory-wise, the key source of inspiration is bio-ecology. In bio-ecology, the niche is a central construct that describes the position of an organism or species in an ecosystem. A similar concept of the niche has been applied extensively in organizational ecology, to describe the position of an organization or organizational form in a population or community, respectively. It is argued that the niche of an organization (or an organizational form, for that matter) is the locus of competition, legitimation and selection (Hannan, Carroll, & Pólos, 2003b). For example, Podolny, Stuart and Hannan (1996), Dobrev, Kim and Hannan (2001b), and Dobrev, Kim and Carroll (2003) have used the concept of the niche as an explanatory variable in an ecological model of survival performance of individual organizations. Moreover, Barnett (1990) and Boone, Wezel and van Witteloostuijn (2004) measure a niche variable at the community and population level of analysis, respectively, in an attempt to explain higher-level organizational diversity. Because an organization's niche describes its position in resource space, it logically follows that niche overlap refers to the extent to which the location of organization *x* in resource space is similar to that of organization *y* (Dobrev, Kim, & Carroll, 2002a; Dobrev, Kim, & Hannan, 2001a). For example, two pharmaceutical firms (say, Pfizer and Bayer) may reveal more or less overlap in terms of types of drugs on offer (niche overlap in product space) or in terms of the countries in which they run sales operations (niche overlap in geographical space). At the population level, lower organizational overlap implies higher organizational diversity. Depending upon environmental conditions, such diversity or overlap may increase or decrease the focal organization's likelihood of survival, or may increase or decrease the likelihood of overlapping entry (Boone, Wezel, & van Witteloostuijn, 2007). With high population-level organizational diversity, overlap will boost legitimation, and hence the likelihood of survival; with low such diversity, overlap implies crowding and competition, thus lowering the likelihood of survival.

Another central concept in organizational ecology is organizational density, defined as the (mere) number of organizations active in a specific organizational population. Population density serves as a surrogate for the difficult-to-observe features of the material and social environment that affect organizational founding and mortality rates, particularly competition and legitimation (Hannan & Freeman, 1989). According to Hannan and Freeman (1987: 918), on the one hand, "if institutionalization means that certain forms assume a taken-for-granted character, then simple prevalence of the form ought to legitimate it." This means that processes of legitimation produce a positive relationship between population density and founding rates. Regarding processes of competition, on the other hand, increasing density implies increasing competition within populations, as more organizations fight for limited resources, which results in declining founding rates (Hannan & Freeman, 1987). The joint forces of legitimation (dominant at low density) and competition (dominant at high density) produce non-monotonic density-dependent processes of organizational entry (reverse U-shaped) and exit (U-shaped), which together generate an S-shaped growth curve of population density. Even though this theory of density dependence has been primarily applied to organizational populations, and very successfully so, recent research illustrates that this argument can also be effectively applied in other settings, such as the birth and death rates of national laws (de Jong & van Witteloostuijn, 2008; van Witteloostuijn, 2003; van Witteloostuijn & de Jong, 2009) and organizational rules (March, Schulz, & Shou, 2000; Schulz, 1998). We believe that density-dependence logic can also fruitfully be used in the study of evolutionary processes within technological populations (cf. Pistorius & Utterback, 1997).

The last concept from organizational ecology that we want to introduce is that of status. It is commonly known that in environments marked by pervasive uncertainty, actors base their future expectations on information about the past. In science, this is referred to as the Matthew effect (Merton, 1968b). Within organizational ecology, this phenomenon is labeled the status effect. In an organizational context, organizations associated with high degrees of status, attract activity, such as, for example, investments (Podolny, 1993), exchange relations (Podolny, 1994), and alliances (Stuart, 1998). Status is also important in the context of technology, as technological development is marked by pervasive uncertainty (Dosi, 1982; Nelson & Winter, 1982; Podolny & Stuart, 1995; Rosenberg, 1996). Due to the inherent uncertainty of technological development, the technical properties or features of technology alone may not serve as a reliable guide for directing technological search and development, and organizations may well forgo superior technical performance to rather accept a package of relatively well-known innovations in an attempt to reduce technological uncertainty (Anderson & Tushman, 1990). Moreover, Podolny and Stuart (1995) and Podolny, Stuart and Hannan (1996) empirically validate that, under uncertainty, the identity or status of actors is important in deciding on technological advancement.

Now that we have briefly explained the theoretical concepts on which this dissertation is based, we can continue with the objective that will guide our subsequent investigation.

1.5 Research objective

For sure, technology is central to evolutionary economics, and received substantial attention in focused studies in organizational ecology and industrial organization. However, by and large, ignoring notable exceptions that will be extensively reviewed later in this thesis, technology and organization are studied rather independently. The reason is that organization science as a whole is rather fragmented, without much cross-fertilization between isolated silos. It is therefore our aim to contribute to the integration of technology in organization science by cross-fertilizing organizational ecology and evolutionary economics into what we label the “ecology of technology”. We formulate our objective accordingly.

Research Objective: *To develop an ecology of technology in organization science.*

That is, in this dissertation, we will provide some of the groundwork that is required for developing an integrated model of technology and organization. After all, according to our opinion, only when the evolution of technology and organization is considered in unison can we fully understand the evolution of either one. To accomplish this objective, we will formulate several research questions that will guide our efforts and break this complex task up into manageable parts. In the final chapter, we will revisit our objective and, in the discussion of the limitations of our study, we also provide some directions to facilitate further development of a model on the co-evolution of technology and organization.

1.6 Research questions

As mentioned, relatively little is known about how technology structures ecological processes across organizations and industries. Our interest lies mainly in the stage when technology is still in its formative stage. After all, in this stage, technological structures are highly fluid and, therefore, subject to influence by stakeholders (e.g., organizations or policy makers). It is for this reason that we want to pay explicit attention to one emerging technology in this dissertation: biotechnology. Biotechnology is posited by many as the technology of the future because it holds the potential to cure (costly) diseases such as cancer and Alzheimer, fight hunger by increasing the yield and nutrition value of crop, and even improve upon humankind (BIO, 2008). Even though we certainly believe that biotechnology will have an important impact on our future, we also want to know what the impact is of biotechnology on our current society. We therefore formulate our first research question as follows.

Research Question 1: *What is the importance of biotechnology?*

This research question will be the focus of Chapter 2. The working assumption (i.e., hypothesis) of this chapter is that biotechnology has indeed a large impact on our everyday lives. Using a diverse array of commercially and freely available databases, we will demonstrate that biotechnology has a strong and increasing impact on numerous socio-economic indicators. This leads us to conclude that biotechnology is a strategic technology that has a large and increasing impact on numerous aspects of our socio-economic environment, which includes the organizational environment and is thus relevant for the domain of organization science.

Considering that biotechnology is indeed a strategic technology that penetrates more and more aspects of our everyday life, then what determines the growth of such an emerging technology? The distinction between an emerging technology and a non-emerging (i.e., mature) technology is that a mature technology follows rather predictable and stable patterns of growth. For example, technological developments within semiconductors follow predictable patterns of growth (i.e., exponential growth). According to Intel co-founder Gordon E. Moore (1965), the capacity of semiconductors roughly doubles every year, which was revised approximately nine years later into a doubling every two years. This was posited as Moore's Law by Carver Head in 1972, a noted computer scientist at Caltech at that time. This translates, on the one hand, into a falling of average prices of semiconductor-related materials, and, on the other hand, into an increase in average performance of semiconductor-related products. Even though there are signs that developments within certain biotechnological components can also be characterized by similar patterns of growth, these do not yet translate into a steady decrease of average prices of biotechnology products or an increase in average performance levels. Hence, biotechnology as a whole cannot be characterized by such growth patterns. We formulate our next research question accordingly.

Research Question 2: *How to study the growth of an emerging technology?*

Even though technology is mainly studied from the academic domain of evolutionary economics, we take a slightly different approach in Chapter 3. That is, we study technology by using logic from organizational ecology. The reason for doing so is that organizational ecology is a rather coherent theory that uses rigorous models that are tightly linked with empirics. Furthermore, organizational ecology is currently going through a process of formalization, where different theory fragments are being integrated into more complete wholes (Hannan, Pólos, & Carroll, 2007), which provides for the perfect opportunity to put forth technology as an vital component that should also be included in the ecological perspective. Hence, using organizational ecology logic, we develop a model to study the growth of an emerging technology. We test this model empirically through a panel regression analysis of patent and patent citation data from the United States Patent and Trademark Office (USPTO). In doing so, we demonstrate that emerging technology can effectively be studied as a technological system composed of a set of interacting technological components. The growth of these components depends on the technology's structural characteristics (i.e., its embeddedness in the larger technological landscape), indicating the path dependent nature of (bio-) technology. In the process, we also add diversity as an important construct in the study of technological growth.

Even though this ecological model already contributes significantly to our understanding of technological growth, it is of a relatively static nature (i.e., we assume that the structural characteristics have a stable effect on the technology's individual components), while an emerging technology is characterized mainly by its non-static nature. Therefore, in Chapter 4, we explicitly consider the dynamic nature of emerging technology. So, we formulate our subsequent research questions as follows.

Research Question 3: *How to study the evolution of an emerging technology?*

In Chapter 4, we distinguish between two stages of technological development (i.e., divergence and convergence), and hypothesize that in the stage of divergence competition mainly occurs between sets of organizations that support alternative technological design configurations, in an effort to establish the supported configuration as the basis of future technological developments. In contrast, in the stage of technological convergence, actors have agreed upon the technological design configuration that will form the basis of future developments. So, on the basis of our model from Chapter 3, we develop a logic that distinguishes between these different stages of technological development. In doing so, we demonstrate that these different stages of technological component are characterized by different processes of competition and legitimation. Our model is thus dynamic in the sense that we allow the structural characteristics (of the technological selection environment) to have a differential effect in the different stages of technological development. Moreover, by further taking technological lineage (i.e., the embeddedness of technological development) into account, we add antecedent and descendant technological diversity as key dimensions of the technological niche, and illustrate the intricate role that diversity plays in technological development. We validate our hypotheses by combining a structural break model with a negative binomial panel regression model that analyzes the rate of entry of patents into the different biotechnological components. Again, we use patent and patent citation data from the USPTO.

On the basis of the insights into the growth and evolution of an emerging technology from Chapters 3 and 4, it is possible to extend our knowledge about processes of legitimation and competition at the organizational level as well. However, before we can do so, we first need to define the technological niche at the level of an individual organization. We thus formulate our next research question accordingly.

Research Question 4: *How can we integrate technology into the theory of the organization-specific technological niche?*

In Chapter 5, we choose to define the organization-specific technological niche using formal logic not only because this connects nicely to the formalization wave that is currently going on in organizational ecology, but this also greatly facilitates the integration of our findings. Because natural language is highly ambiguous, it is possible to formulate highly eloquent arguments that are logically flawed. This makes a process of logical formalization valuable, as it requires explicating all underlying assumptions that are used in the argumentation. We formalize the theory of the organization-specific technological niche as conceived by Podolny, Stuart, and Hannan (1996), to develop a formal argument regarding the role of technology in co-determining organizational performance that is logically sound and complete. We add technological quality as a dimension to the technological niche (besides crowding and status) and explicate how uncertainty mediates the relationship between the organization's technological quality, status, and performance. Moreover, we argue that crowding or niche overlap not always results in competition, but, in certain conditions, can also lead to legitimation effects as a result of positive spillovers. In doing so, we demonstrate how formal logic can be used in the process of theory analysis and how it facilitates theory extension. As mentioned, this also connects to the current wave of logical formalization that is ongoing in organizational ecology.

After formalizing the technological niche, we are fully equipped to integrate our findings from Chapters 3 and 4, and thus posit our next research question as follows.

Research Question 5: *What are the consequences of integrating several technological insights into the theory of the organization-specific technological niche?*

In Chapter 6, we integrate our insights about the growth and evolution of technology into our formal theory fragment from Chapter 5, hereby extending the theory of the organization-specific technological niche. Basically, we extend our arguments by using a total of four assumptions, namely, the existence of (1) multiple technological systems, (2) different stages of technological development, (3) different levels of uncertainty, and (4) different growth rates. On the basis of these rather simple and straightforward assumptions, we can significantly extend the theory of the technological niche. Not only by pointing to the important role that the stage of technological development plays in the formalized arguments of status and crowding, but also by adding two additional dimensions to the organization-specific technological niche, namely technological diversity and technological opportunities. The dimension of technological diversity is threefold. First, focal technological diversity signifies the extent to which an organization's technological developments are situated in different technological domains. Second, antecedent diversity refers to the extent to which the organization's knowledge originates from different technological domains. Third, descendant diversity refers to the extent to which the organization's technology is diffused throughout the technological landscape. Technological opportunities refer to the extent to which innovations within a certain domain are easier to accomplish. In all, we posit that technology has a highly intricate role in organizational performance, and structures ecological processes within and between organizational populations.

Clearly, even though the theoretical discussion of the previous chapters already contributes greatly to our understanding of the role of technology in organizational performance, we need statistical evidence to back our arguments. Hence, our next research question becomes as follows.

Research Question 6: *Can we find proof for our extended theory of the organization-specific technological niche?*

Our extended model from Chapter 6 will be empirically tested in Chapter 7, by investigating the effects of the different dimensions of the organization-specific technological niche on organizational biotechnology innovation. We test our model by analyzing all organizations that have been awarded more than 10 biotechnology patents during the period of 1980-2005. Through a sophisticated negative binomial panel regression analysis of 935 organizations, we find strong support for many of our hypotheses. In doing so, we demonstrate the added value of a structural perspective towards technological change in explaining processes of competition and legitimation of individual organizations. Hence, cross-fertilizing organizational ecology and evolutionary economics appears to hold much promise. Moreover, it seems to suggest that technology might be an important factor in closing the chasm between organizational adaptation and environmental selection. In the concluding chapter, we consider the implications for the study of technological and organizational (co-) evolution. Hence, our final research question can be stated as follows.

***Research Question 7**: What are implications for the study of the co-evolution of technology and organization?*

Finally, Chapter 8 discusses the implications of our findings. That is, we propose a general framework that can be used to investigate the co-evolutionary processes that exist between technology and organization. More specifically, by conceiving technology and organization as multileveled hierarchies, it is possible to delineate the co-evolutionary links and define some general characteristics that are deemed important in the study of the co-evolution between technology and organization. Additionally, on the basis of the design limitations of our study, we also consider important avenues for future research

1.7 Organization of this dissertation

To recap, the next chapter will present evidence to indicate the increasing importance of biotechnology in our everyday lives. Next, Chapter 3 will develop an ecological model to study the growth of emerging technology, while Chapter 4 will make this model more dynamic to enable a better investigation of the evolution of emerging technology. To facilitate integration of our findings from Chapters 3 and 4, through a process of logical formalization, Chapter 5 will develop a formal theory of the organization-specific technological niche. Then, in Chapter 6, we will actually integrate our main findings about the growth and evolution of emerging technology into this formal theory. Next, Chapter 7 will test whether our extended model holds when subjected to a thorough empirical test. Finally, Chapter 8 will discuss our main findings in the context of our objective, propose a general framework to study the process of co-evolution of technology and organization at multiple levels of analysis, and provide directions for future research.

Chapter 2

Biotechnology

2.1 Introduction

Even though mankind has utilized biological processes for over 6,000 years (BIO, 2008), the first phase of the biotechnology revolution only started in the mid-1930s (Goujon, 2001). This phase can be characterized by the term molecular biology, and is the result of a convergence of several previously distinct biological disciplines, such as biochemistry, genetics, microbiology and virology. The discovery of deoxyribonucleic acid (DNA) in 1953 by James Watson and Francois Crick initiated the second phase of the biotechnology revolution, marking the beginning of the modern era of genetics. This era received a major impulse from genetic modification, represented by recombinant DNA (rDNA) technology. rDNA technology was first conceived by Herbert Boyer and Stanley N. Cohen in 1972, and has dramatically changed the field of biological sciences, by opening the door to genetically modified organisms.

The major finding in biotechnology in the last five to ten years is the principle of biological universality, or the striking similarity of the cell (Horvitz, 2002). Unity of life at the cellular level provides the foundation for biotechnology. All cells have the same basic design, are made of the same construction material, and operate using essentially the same processes. DNA, the genetic material of almost all living species, directs cell construction and operation, while proteins do all the actual work. Because cells and biological molecules are extraordinarily specific in their interactions, biotechnology products can solve specific problems, and generate fewer side-effects and unintended consequences than other approaches (BIO, 2006). Biotechnology is expected to have a major impact on our society, and has been suggested as the solution to battle increasing healthcare costs by curing costly diseases and enabling predictive, preventive, and personalized medicine.

The structure of this chapter is as follows. First, in Section 2.2, we will give a brief introduction of what biotechnology precisely is. Next, Section 2.3 discusses the increasing importance of biotechnology by investigating the economic and social impact of biotechnology. We will dig deeper into the position of biotechnology from a purely technological perspective in Section 2.4. Finally, Section 2.5 considers the future of biotechnology by contemplating the advancements within synthetic biology.

2.2 What is biotechnology?

Biotechnology essentially refers to all technology that is based on biology. Hence, biotechnology is the technology of the living world. According to this definition, biotechnology is far from being a new phenomenon. After all, human kind has been using biological processes for over 6,000 years to leaven bread, to ferment beer and to produce wine (BIO, 2008). However, what has changed during the last century is that we have gone from the use of biological processes at the macro level (i.e., by using whole organisms, such as yeast) to the use of biological processes at the micro level (i.e., by using processes that occur at the cellular and molecular level, so within organisms). Hence, a modern definition of biotechnology can be stated as follows:

"[T]he use of cellular and bio-molecular processes to solve problems or make useful products" (BIO, 2008: 1).

2.2.1 How does biotechnology work?

In the mid-19th century, it was discovered that all organism are composed of cells, and that all cells are created by cells. This implies that the cell is the basic building block of life. Essentially, there are two kinds of cells: (1) prokaryotic cells, and (2) eukaryotic cells. Prokaryotes refer to the group of organisms (usually unicellular, and mostly bacteria) that lack a cell nucleus. In contrast, eukaryotes (e.g., plants, animals, and humans) are multi-cellular organisms with different types of specialized cells that all originate from the same basic, undifferentiated stem cells.[2] As a result, eukaryotic cells are much more complex, the main difference being that they contain a nucleus or command center that contains its entire DNA (i.e., the organism's genome or complete collection of genetic material) that instructs the cell what to do in specific situations.[3] The development of a multi-cellular organism from a single cell involves the processes of cell proliferation and cell differentiation. Cell proliferation refers to the process where cells replicate many times. Cell specialization or differentiation refers to the process where a less specialized cell (e.g., a stem cell) differentiates into a more specialized cell (e.g., a human nerve, blood, heart, or muscle cell).

Unspecialized or stem cells have three properties that distinguishes them from specialized cells, which are: (1) stem cells are capable of dividing and renewing themselves for long periods (i.e., proliferation), (2) stem cells are unspecialized, and (3)

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[2] Human embryonic stem cells (ESC) can differentiate into all kinds of different cells, such as, for example, brain cells, heart cells, nerve cells, tissue cells, and liver cells. In contrast, adult stem cells (ASC) are undifferentiated cells that have more limited flexibility. Currently, scientists are investigating processes of cell differentiation and de-differentiation. Scientist had assumed that differentiated cells could not be reverted (i.e., de-differentiated) into unspecialized cells. The birth of Dolly proved this to be an incorrect assumption, when Scottish scientists cloned Dolly by using an adult stem cell through a process of somatic cell nuclear transfer. It was because of this reason that Dolly was special, not just the fact of cloning per se.

[3] Because prokaryotic cells do not have a nucleus, all DNA is condensed into what is called a nucleoid contained in the cytoplasm of the cell.

stem cells can give rise to specialized cell types, such as a heart muscle cell that pumps blood through the body, a red blood cell that carries oxygen molecules through the bloodstream, or a nerve cell that can fire electrochemical signals to other cells that allow the body to move or speak. There is a distinction between embryonic stem cells and adult stem cells, the difference being that adult stem cells typically generate the cell types of the tissue in which they reside. For example, a blood-forming adult stem cell in the bone marrow normally gives rise to the many blood cells, such as red and white blood cells. The differentiation of stem cells into specialized cells (i.e., cell differentiation) occurs through a combination of internal and external signals. The internal signals are controlled by a cell's DNA, which carries the genetic instructions of the cell. External signals include chemicals secreted by other cells, physical contact with neighboring cells, and certain molecules in the microenvironment. In all, cells undergo four processes, which are: (1) cell growth, (2) cell reproduction, (3) cell differentiation, and (4) cell death.

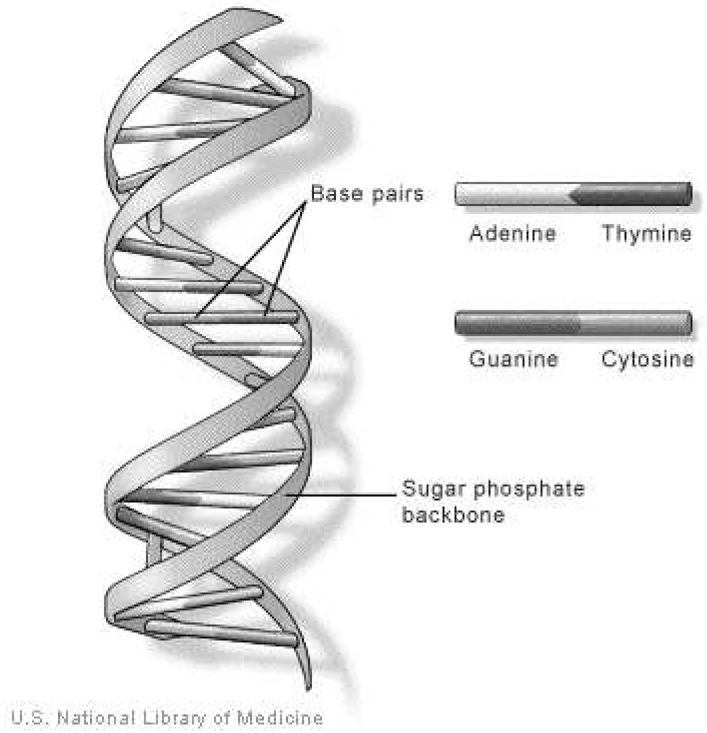

Figure 2.1 The double helix structure of DNA (source: U.S. National Library of Medicine)

2.2.2 How are the DNA instructions actually turned into proteins?

A gene refers to a particular section of our DNA that contains the process instruction to fabricate a particular protein. The Human Genome contains approximately 25.000-30.000 genes, encoded in a total of approximately 3 billion base pairs of DNA. DNA has a double helix structure and is composed of so-called base pairs (i.e., AT or GC, where the initials stand for Adenine, Thymine, Guanine, and Cytosine, respectively). These base pairs are combined using sugar and phosphate molecules to actually form the double helix structure, as can be seen in Figure 2.1.

Under the right conditions (i.e., a combination of internal and external signals), the double helix of DNA will unravel itself into two strands, and mRNA (i.e., messenger ribonucleic acid) is created from one strand of DNA. That is, the DNA serves as a template to create a strand of genetic instructions or mRNA. The mRNA then travels outside the cell nucleus, where it is read by another cell structure (i.e., ribosome) that produces the protein by combining different types of amino acids. This process is displayed in Figure 2.2.

Different combinations of amino acids result in different types of proteins. Because proteins are encoded in our genes, there should be an equal amount of proteins as genes in the Human Genome. However, post-translation modifications add to protein diversity. As a result, the human proteome (i.e., the complete human protein system) is a highly dynamic and complex system that contains 100s of thousands of different proteins. Some of the better known protein types are antibodies, enzymes (chemical reactors), messengers, structural components, and transport/storage proteins. Due to the important role of protein the in cellular processes (i.e., proteins provide all functionality for cellular processes), understanding cells means understanding proteins. In turn, understanding proteins implies understanding genes, as proteins are an expression of the genes.

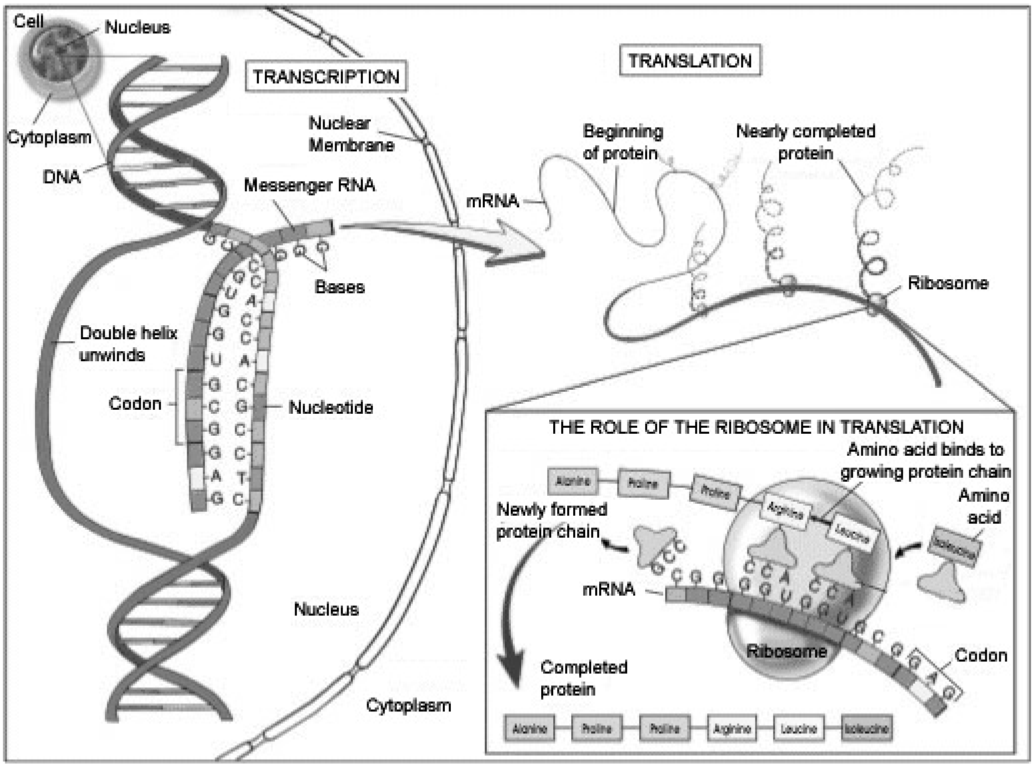

Figure 2.2 Protein synthesis (source: US National Institute of Health)

2.2.3 The unity of life on a cellular level

As mentioned previously, the most important principle of biotechnology is the unity of life at cellular level (BIO, 2008; Horvitz, 2002). The cell is the fundamental unit of life and all cells have the same basic design. That is, all cells have the same basic components (e.g., DNA, rRNA, ribosome, and proteins) that interact in the same way.[4] So, millions of years of evolution have resulted in highly sophisticated molecular systems (Lauffenburger, 2005). Because almost all cells speak the same genetic language, DNA from one cell can be used by any other cell (even a completely different cell from a completely different species). This feature makes DNA the cornerstone of modern biotechnology, as it is the machine language of biological processes. It effectively allows biotechnologists to recombine biological processes from different organism (such as plants, animals, insects, and humans) at the molecular level. Biotechnology thus gives us the ability to influence evolution at the molecular level. And, due to the fact that the genetic instructions that are encoded in an organism's DNA or genome are so specific, biotechnology products can often solve problems more effectively (i.e., with fewer side-effects than other approaches). In fact, the best words to describe today's biotechnology are specific, precise, and predictable (BIO, 2008). Box 2.1 provides an overview outline of some of the major historic events that characterize biotechnology's evolution.

Biotechnology's condensed timeline
8000bc Humans domesticate crops and livestock
4000bc Biotechnology first used to make bread and beer
1590-1608 The microscope is invented
1663 Cells are discovered
1761 Successful cross breeding of different species of crop plants
1830 Proteins are discovered
1833 Discovery of the cell nucleus
1838 Cell is the organization of all living things
1839 All organisms are composed of cells
1858 All cells only arise from pre-existing cells
1859 Darwin's theory of evolution
1865 Mendel's law of inheritance
1879 Chromosomes are discovered
1919 The word 'biotechnology' is first used in print
1938 The term 'molecular biology' is coined
1941 The term 'genetic engineering' is first used

[4] Clearly, we refer here to the design configuration of cells that are of the same type (e.g., prokaryotic and eukaryotic cells), even though design configurations of cells of different types are also highly similar.

1944 Discovered that DNA carries genetic information
1953 Double helix structure of DNA discovered
1958 DNA is made in a test tube
1960 Messenger RNA is discovered
1972 First recombinant DNA molecule created
1973 Technique to cut and paste DNA (i.e., recombinant DNA or rDNA) perfected
1975 Conference to discuss rDNA and develop safety protocols
1976 First biotech company (i.e., Genentech) founded
1980 The US Supreme Court rules that modified organisms can be patented
1980 US Bayh-Dole Act: grant recipients own federally funded inventions
1980 Polymerase Chain Reaction (PCR) invented, a technique for copying DNA
1982 First biotech drug (i.e., Genentech's and Lilly's human insulin) approved by the FDA
1983 The first genetic markers for specific inherited diseases are found
1988 The US Patent and Trademark Office grants Harvard University a patent for a mouse
1988 United States launches the Human Genome Project
1989 Plant Genome Project begins
1990 Official start of the Human Genome Project
1996 First Biotechnology crops commercially grown
1997 Dolly the sheep (cloned using an adult stem cell) is unveiled in Scotland
1998 First complete animal genome is sequenced
1998 Discovery of how to isolate human embryonic stem cells
2000 First complete map of a plant genome is developed
2001 Draft version of the complete human genome is published
2002 First draft of a functional map of the yeast proteome (i.e., complete protein system)
2003 The Human Genome Project is completed
2004 The first biotech pet (i.e., a fluorescent fish) hits the North American market
2005 Skin cells dedifferentiated into Embryonic Stem Cells (ESC) using existing ESC
2006 Pig developed that produces high levels of omega-3 fatty acids
2007 Eucalyptus tree developed that ingests up to three times more carbon dioxide
2007 Skin cells dedifferentiated into ESC without using existing ESC
2008 Craig Venter's genome synthesized (proof DNA carries genetic instructions)

Box 2.1 Biotechnology's timeline (source: BIO, 2008; Biotechnology Institute, 2009)

2.3 The importance of biotechnology

Not only will biotechnology be important for the future of human kind, it already has a major impact on our current society. As we will demonstrate in this section of the chapter, according to numerous socio-economic indicators, the activity within biotechnology is increasing at a rapid pace. Because most of these figures speak for themselves, we will not discuss them in great detail.

From a financial perspective, we can get an idea of the importance of biotechnology by looking at the market capitalization of publicly traded biotechnology firms. According to Bioworld (2008), a leading biotechnology news provider and information source, the market capitalization of biotechnology stocks tracked was $360 billion in April 2008. Figure 2.3 present the evolution of the market capitalization of biotechnology firms from 1994 until 2006. As becomes clear from this figure, there has been a sharp increase over the recent years in absolute terms. From 1994 to 2006, market capitalization has increased more than seven-fold. Especially the sharp increase in 2000 is noteworthy, and illustrates that 2000 was a highly successful year for the biotech industry.

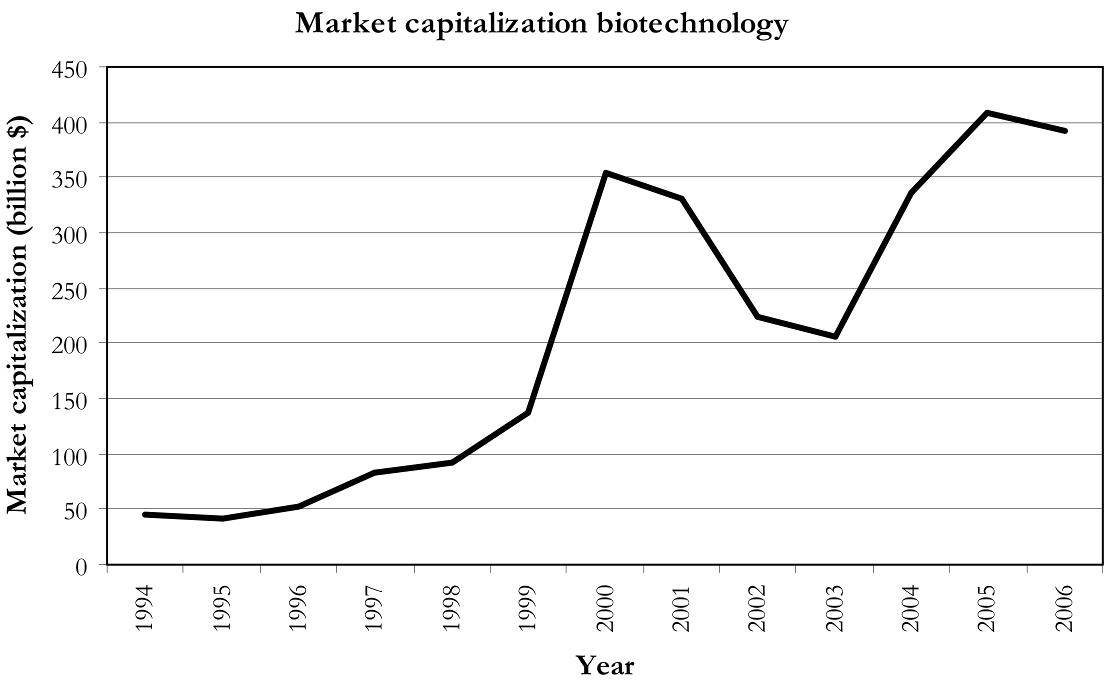

Figure 2.3 Market capitalization (BIO, 2008)

In relative terms, the value increase remains highly impressive. Even though biotechnology shares obviously move up and down with the stock exchange's general climate, biotechnology outperforms the average technology fund. This is illustrated in Figure 2.4, were we juxtapose the relative increase in the market capitalization of biotechnology stocks with the NASDAQ composite index from 1994 to 2006.

There are two reasons for the sharp increase in market capitalization in 2000. First, this is due to an increase in biotechnology investments, as can be seen in Figure 2.5. Even though 2000 was an extraordinary year for biotechnology investments that has not been surpassed in 2001 to 2004, the general trend is that biotechnology investments are steadily increasing. The second reason is a sharp increase in stock evaluations. Despite some analyst's claims, biotechnology is, however, not just thriving on expectations. After all, biotechnology is not merely growing strong in financial terms, but also displays a strong growth in other areas, such as, amongst others, in terms of actual products on the market, as can be seen in Figure 2.6.

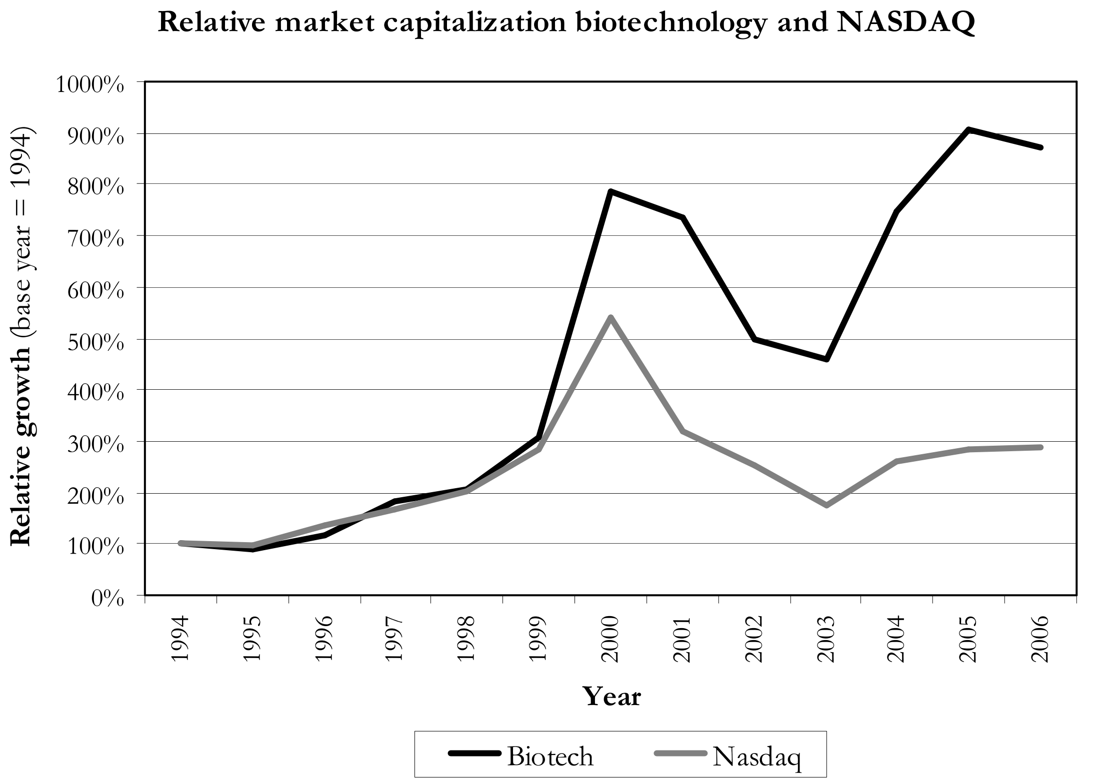

Figure 2.4 Relative increase in biotechnology's market capitalization and the NASDAQ composite index, base year = 1994

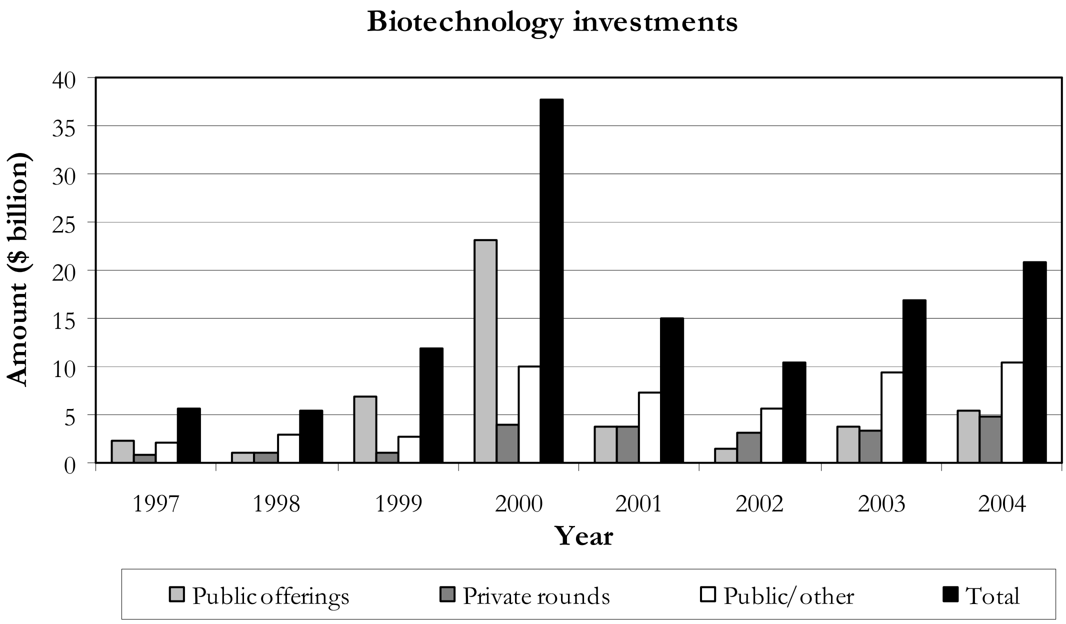

Figure 2.5 Biotechnology investments (source: Bioworld)

This strong growth can also be observed from the number of alliances formed by biotechnology organizations, which has also increased sharply over the recent years, as can be seen in Figure 2.7. Again, a surge in activity can be noted in the year 2000, stressing the importance of that year for the biotechnology industry. Despite the fact that the subsequent years have not been able to top 2000, again, the general trend is clearly an increasing one. The figure also demonstrates that the alliance activity is not only the result from cooperation between biotechnology and pharmaceutical organizations. Even though the early years of alliance activity in biotechnology was mainly driven by biopharmaceutical alliances (i.e., alliances between pharmaceutical firms and biotechnology firms), recent years demonstrate that alliance formation in biotechnology is becoming more independent from cooperation with pharmaceutical firms. This implies that there is an increase in the formation of alliances between biotechnology and non-pharmaceutical firms (i.e., alliance activity is increasing among biotechnology firms, between biotechnology firms and universities, and between biotechnology and non-pharmaceutical firms).

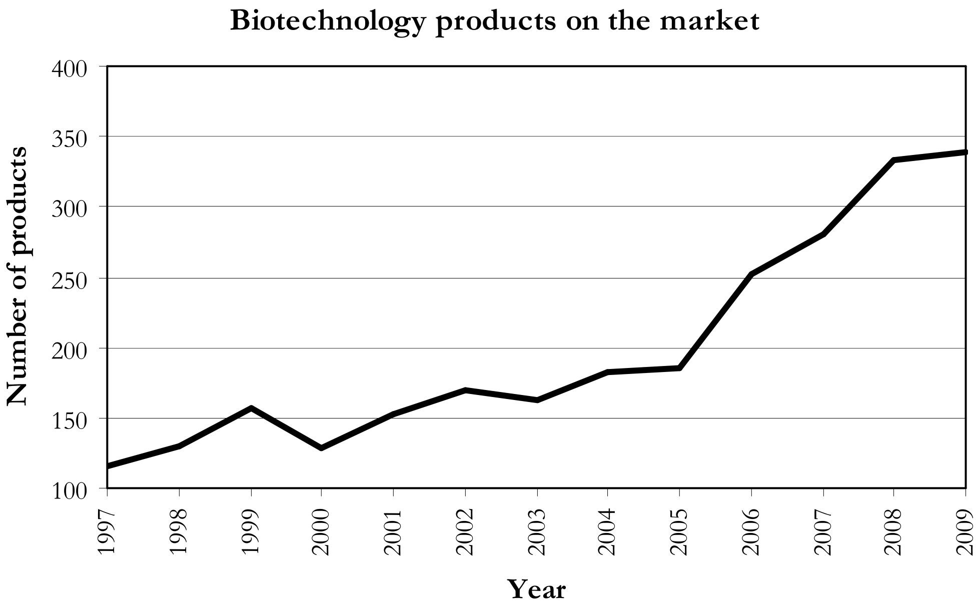

Figure 2.6 Biotechnology products on the US market (source: Bioworld)

Besides an increase in alliances, we can also witness a sharp increase in merger and acquisition activity. In Figure 2.8, we graphically display the number mergers and acquisitions where the primary target or acquirer was a biotechnology firm. Because different databases contain different statistics, due to differences in coverage and coding strategies, we include both the data from Thomson Banker One and Bioworld. Even though these databases display different patterns, the general trend is a strong increase in M&A activity over the recent years.

Furthermore, we have also conducted a query on Google to determine the attention (i.e., the number of pages devoted to biotechnology) that biotechnology receives on the World Wide Web. The results of this query are displayed in Figure 2.9. As can clearly be observed in this figure, the last three years the attention for biotechnology is increasing exponentially. Even though it is impossible to draw any strong conclusions from these figures, it does indicate the growing attention that biotechnology receives.

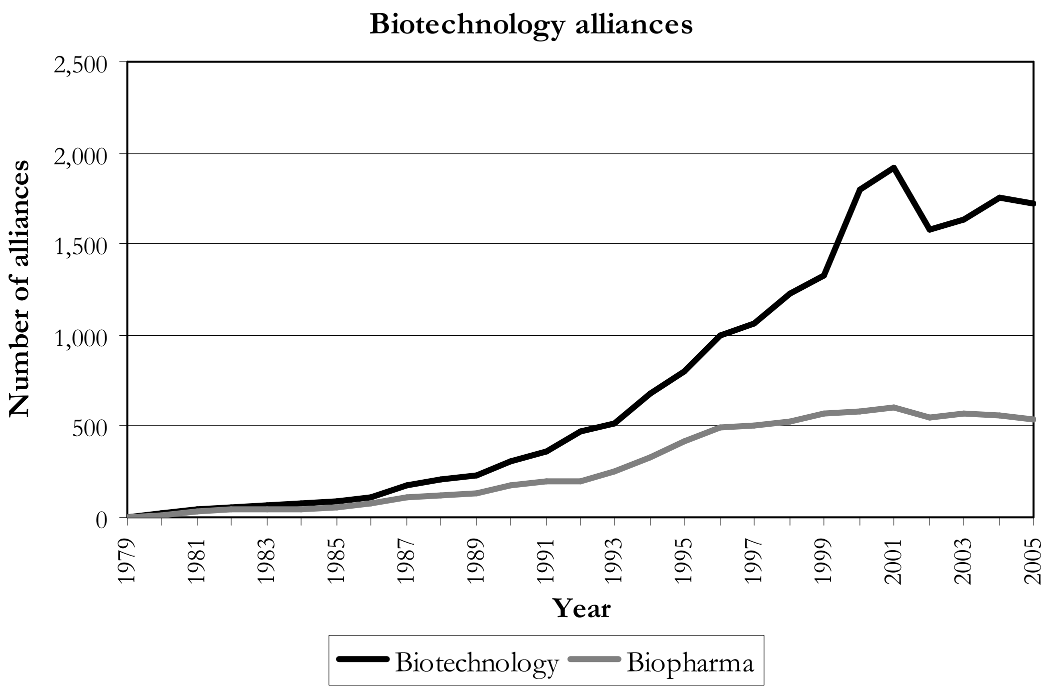

Figure 2.7 The evolution of biotechnology and biopharmaceutical alliances (source: Recap)

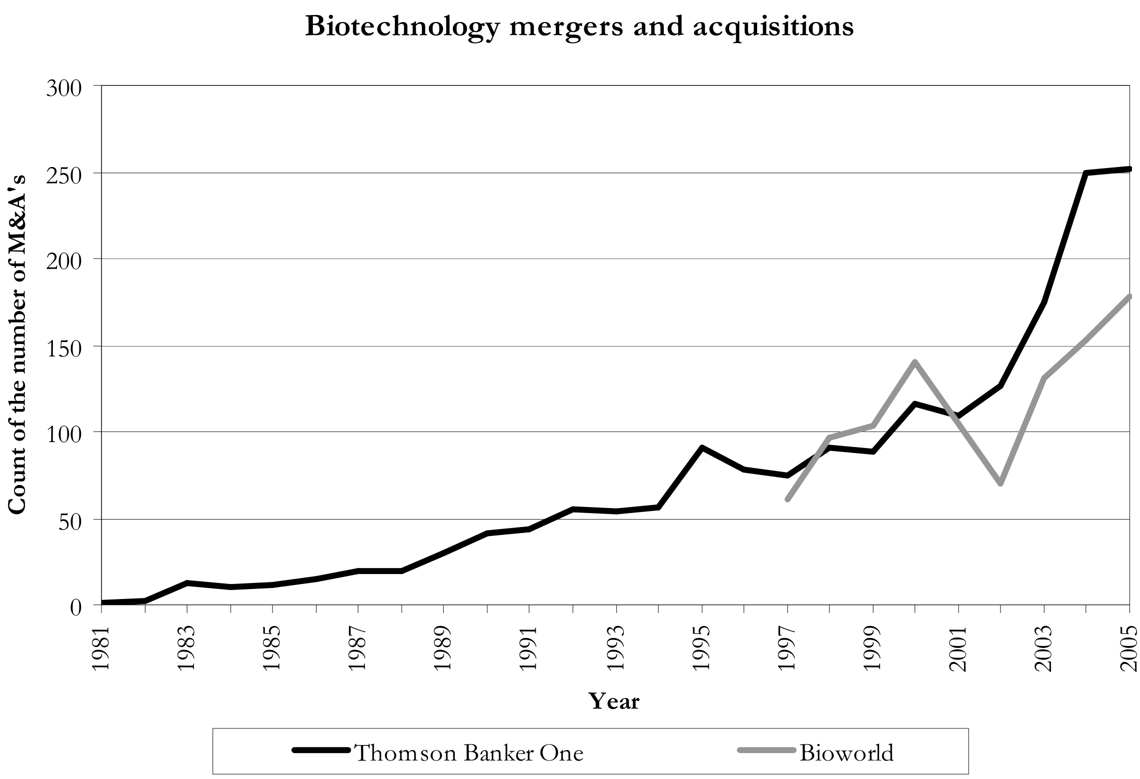

Figure 2.8 Number of M&As (source: Thomson Banker One & Bioworld)

If we look at the number of scientific publications, the year 2000 was not out of the ordinary. As can be seen in Figure 2.10, the number of publications increases steadily in the period 1980-2008. If we assume that scientific knowledge translates into useful products and processes with a certain time lag, as many scholars do, this implies that the impact of biotechnology will continue to increase over the coming years.

When looking at the technological knowledge production (i.e., patents), we also see a sharp increase. However, we can also observe a decline in the last years of observation (see Figure 2.11). This is due to a number of reasons, which are, amongst others, the completion of the Human Genome Project in 2003 (Lawrence, 2004), stricter examination guidelines for biotechnology patents at the USPTO (Barfield & Calfee, 2007), the Bush administration's ban on stem cell research, and Bush's closure of the loophole in drug patents in 2002.[5]

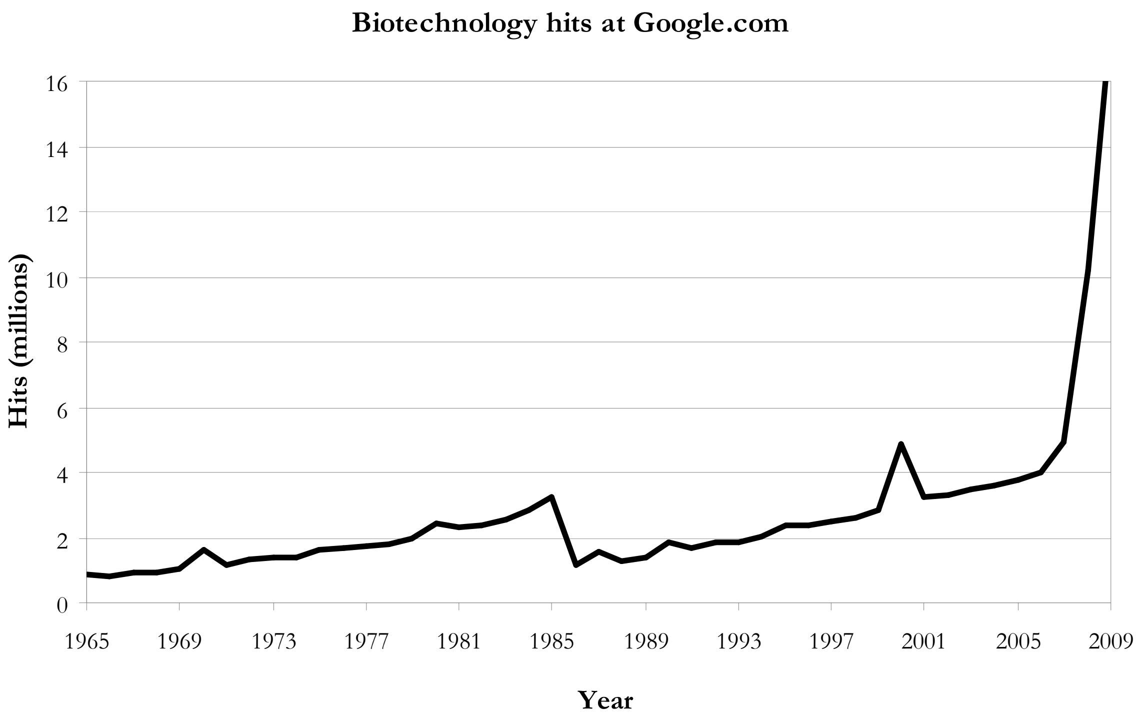

Figure 2.9 Number of biotechnology hits at Google.com per year (the search term for 2005 was as follows: "biotechnology AND year AND 2005")

[5] Closure of the loophole in drug patent was part of a plan to speed up the process of getting generic drugs to the marketplace. The new rules make it clear that drug companies cannot file patents on such product aspects as packaging changes, metabolites, and intermediates that are unlikely to represent significant innovations to the original drug.

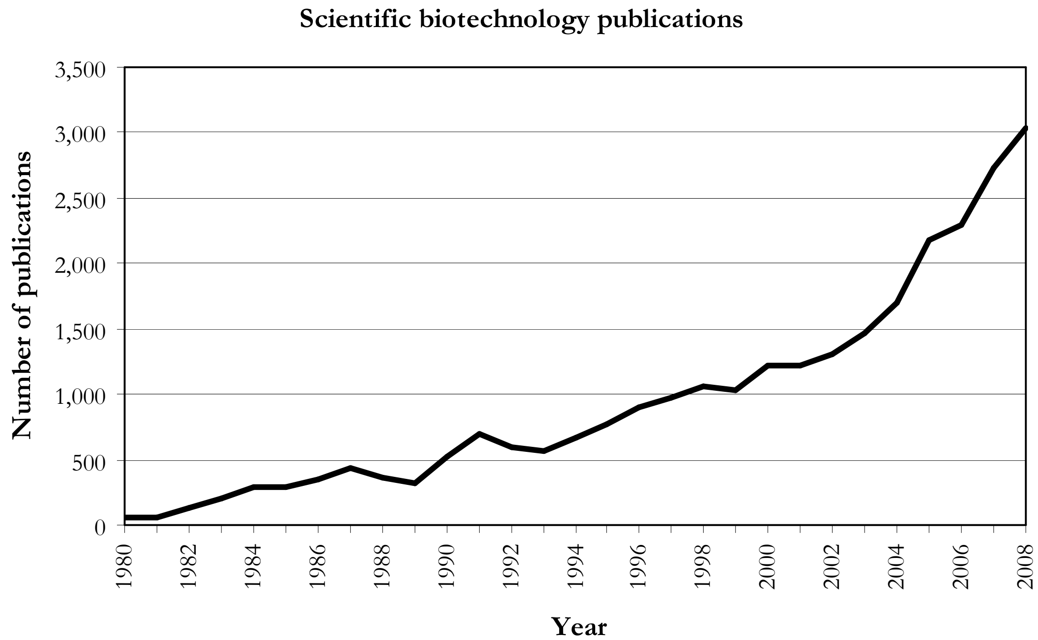

Figure 2.10 The number of scientific publications on biotechnology per year (source: ISI Web of Knowledge; all databases where topic is biotechnology)

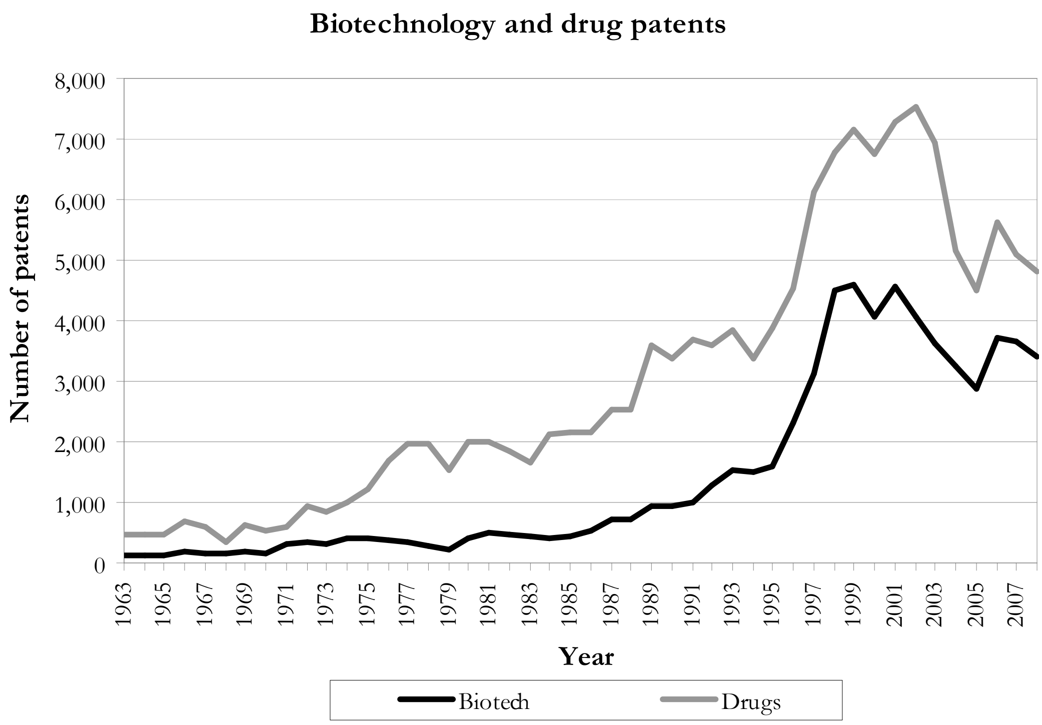

Figure 2.11 The total number of USPTO Biotechnology (i.e., class 435 + 800) and Drugs (i.e., class 435) patents per year

To illustrate that the reduction in drug and biotechnology patents is not tied to a general patenting trend, Figure 2.12 displays the growth of biotechnology and drug patents relative to the total number of patents issued by the USPTO.

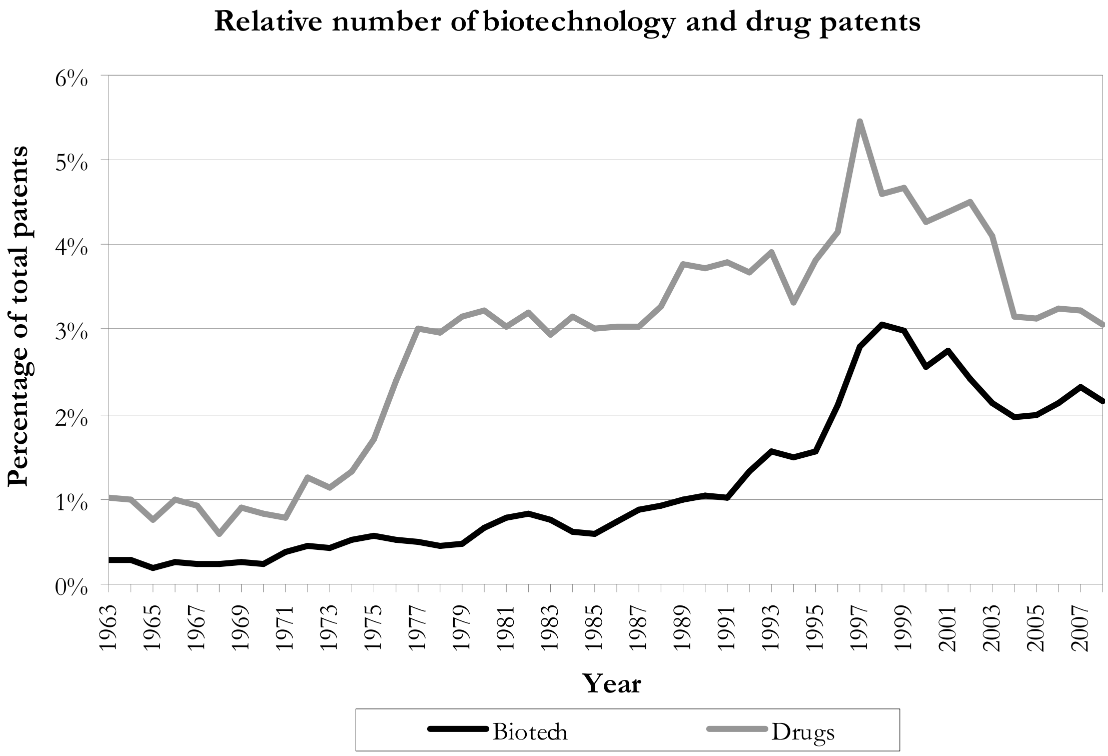

Figure 2.12 The number of USPTO Biotechnology (i.e., class 435 + 800) and Drugs (i.e., class 435) patents per year relative to the total number of USPTO patents

2.4 The position of biotechnology in the technological landscape

In this section, we will consider the evolution of biotechnology's position in the total of technological developments (i.e., in the overall technological landscape). The position of a focal technology in the overall technological landscape indicates the extent to which the focal technology forms an essential and integrated part of the whole of technological development. On the basis of this information, we are able to deduce the role of biotechnology in the historic and current technological structure of our society. To represent this information, we will make use of the concept of a technological network, which was first developed by Podolny and Stuart (1995). In this work, the authors use the concept of a technological network to represent individual inventions (i.e., the nodes of the network) and the technological linkages that exist between these inventions (i.e., the ties of the network). To construct the network, the authors use patents to represent the inventions, and patent citations to represent the technological ties between these inventions. Subsequently, in cooperation with Mike Hannan (Podolny et al., 1996), the authors use firms to represent the nodes of the network, again using patent citations to represent the linkages between the nodes. Here, we take this methodology one step further, and argue that the nodes of the network can also be represented by technologies or technological domains (e.g., biotechnology or semiconductors). Again, on the basis of patent and patent citation data, we can construct technological networks that represent the structure of the overall technological landscape. On the basis of these networks, it is subsequently possible to determine the evolution of a technology or a technological domain (e.g., biotechnology) in the overall (patented) technological structure. The position of a technology in this network can be used to infer the role of the technology in the overall technological landscape. For example, according to the social network literature (Wasserman & Faust, 1994), the more central a focal technology the more important the role of this technology in the technological landscape. Hence, on the basis of a simple visual inspection of these technological networks, we can determine the role of biotechnology in the whole of technological development.

To make the data manageable, we distinguish between a total of six five-year periods, ranging from 1976 until 2005. For these periods, we display the core structure of the technological landscape, by using patent and patent citations data from the USPTO. More specifically, we position technologies using 'spring embedding' on the basis of geodesic distances in Net Draw (Borgatti, Everett, & Freeman, 2002). We distinguish between higher lever technological categories and lower level technological domains using the classification system developed by Hall, Jaffe, and Trajtenberg (2001b). Within this classification system, technological domain 33 refers to biotechnology, is composed of USPTO patent classes 435 and 800, and belongs to technology category 3, named 'Drugs and Medical'.

In these networks, the size of the nodes is based on the relative number of patents of this domain, and thus reflects the size of the technological domain relative to all other domains. The linkages between the domains represent citations patterns and determine the relative position of the domain in the plots. For each network plot, we employ a unique cut-off value to represent the core configuration of the technological landscape. The reason for doing so is that the number of citations increases substantially over subsequent years, and employing the same cut-off value results in highly dense (sparse) and non-informative network images in later (earlier) periods. In the network plots below, we indicate the position of biotechnology using a larger typeface. These figures clearly illustrate three points. First of all, the structure of the technological landscape is highly stable over time, which suggests the existence of stable technological (design) configurations at aggregate levels of analysis. This is illustrated by the fact that many ties between components remain stable over time. For example, the tie between "Biotechnology" and "Miscellaneous-chemical" exists in all periods. This naturally leads us to our second point, which is that technologies are embedded within a larger technological environment.[6] Third, biotechnology's position changed in the early 1990s. Until then, biotech was only connected to "Miscellaneous-chemical". Since the early

[6] Remember that the network plots only represent the core of the technological landscape. If all linkages between technologies would be included, the embedded nature of technological development would be much more profound.

1990s, connections with "Organic Compounds" and "Drugs" were added. This can be seen as a sign that biotech is now starting to move closer to the core structure of the network, by creating strong triads or Simmelian ties (Simmel, 1950) with "Organic Compounds", "Miscellaneous-chemicals", and "Drugs". However, notwithstanding this shift, biotech has still a long way to go before this technology can be regarded as really core. For example, consider the distinction between the evolution of biotechnology versus the evolution of "Semiconductor Devices". This latter domain has evolved from a peripheral position at the edge of the network to a highly central position in the core of the network. Hence, if the impact of biotechnology is expected to be of the same or greater magnitude as "Semiconductor Devices", it will surely take many years before biotechnology is at its peak influence. In the network plots we only display the technological domains, without reference to the technological category to which they belong. This information is provided in Appendix A, while some descriptive statistics about the (relative) size and importance of the domains in the different periods are provided in Appendix B.

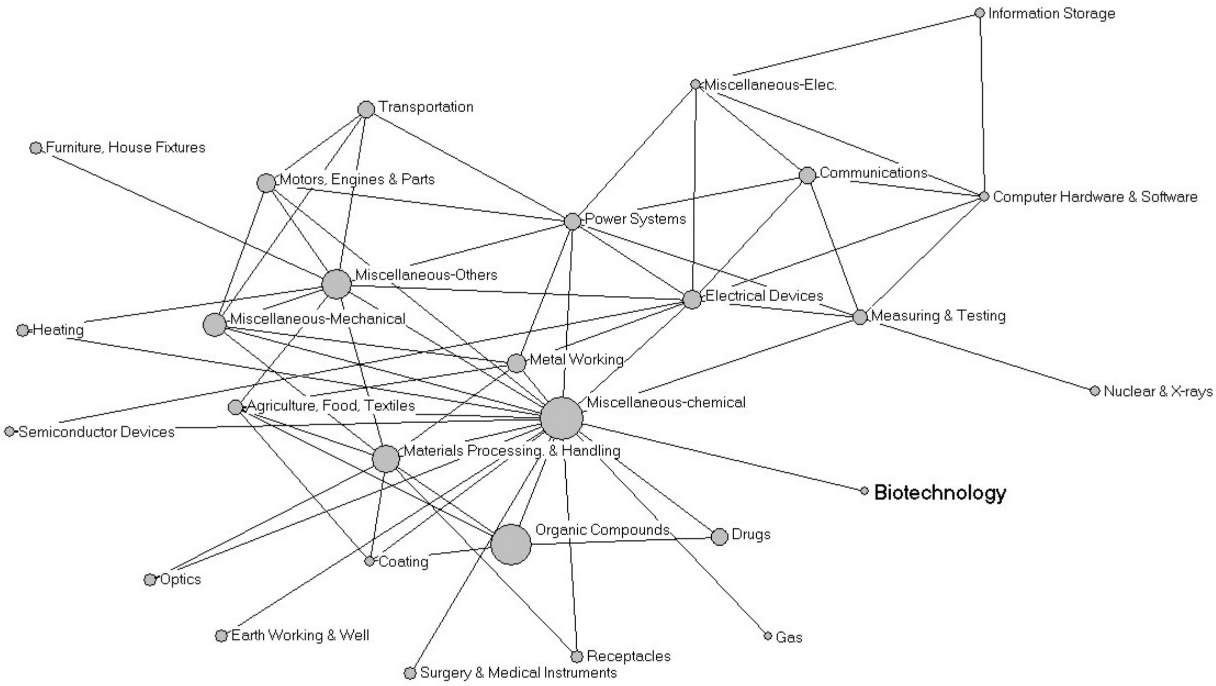

Figure 2.13 Plot of the core of the technological landscape of 1976-1980 (500+ citations)

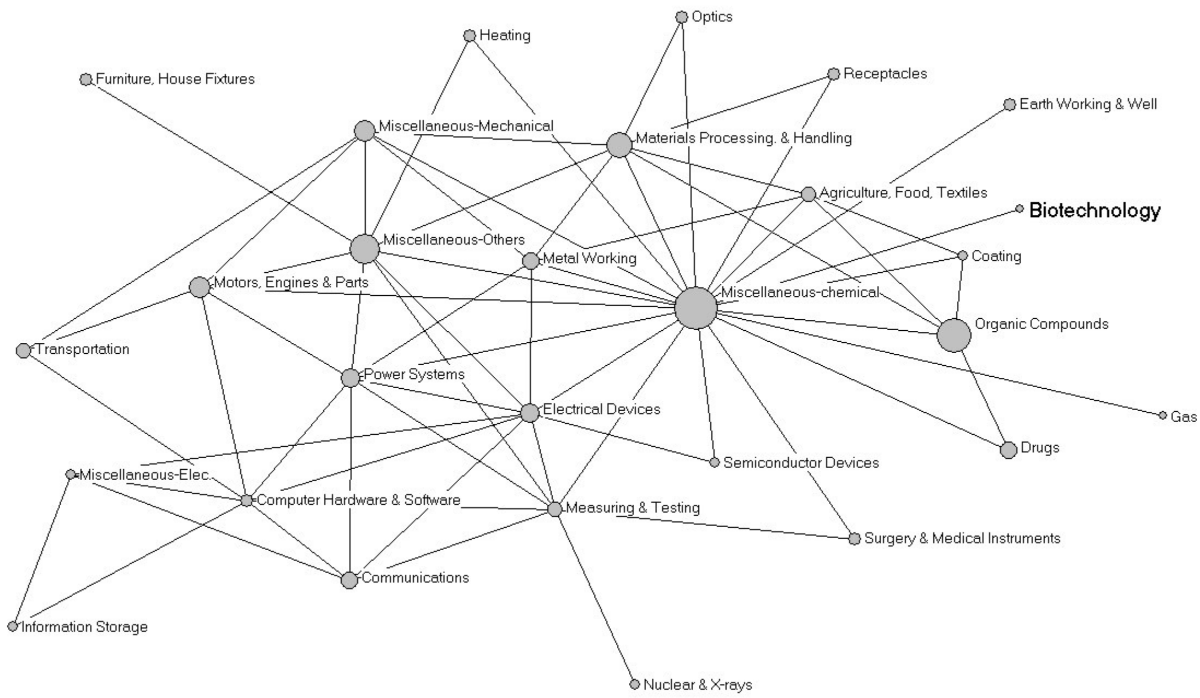

Figure 2.14 Plot of the core of the technological landscape of 1981-1985 (750+ citations)

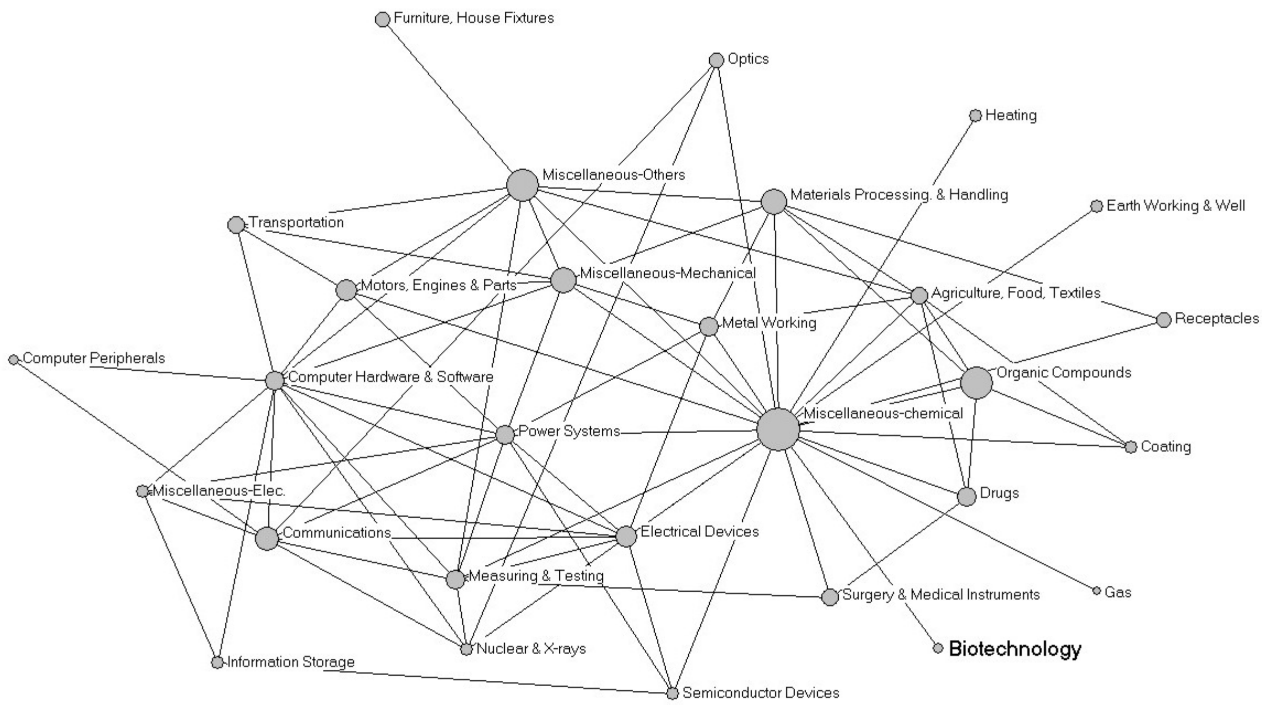

Figure 2.15 Plot of the core of the technological landscape of 1986-1990 (1250+ citations)

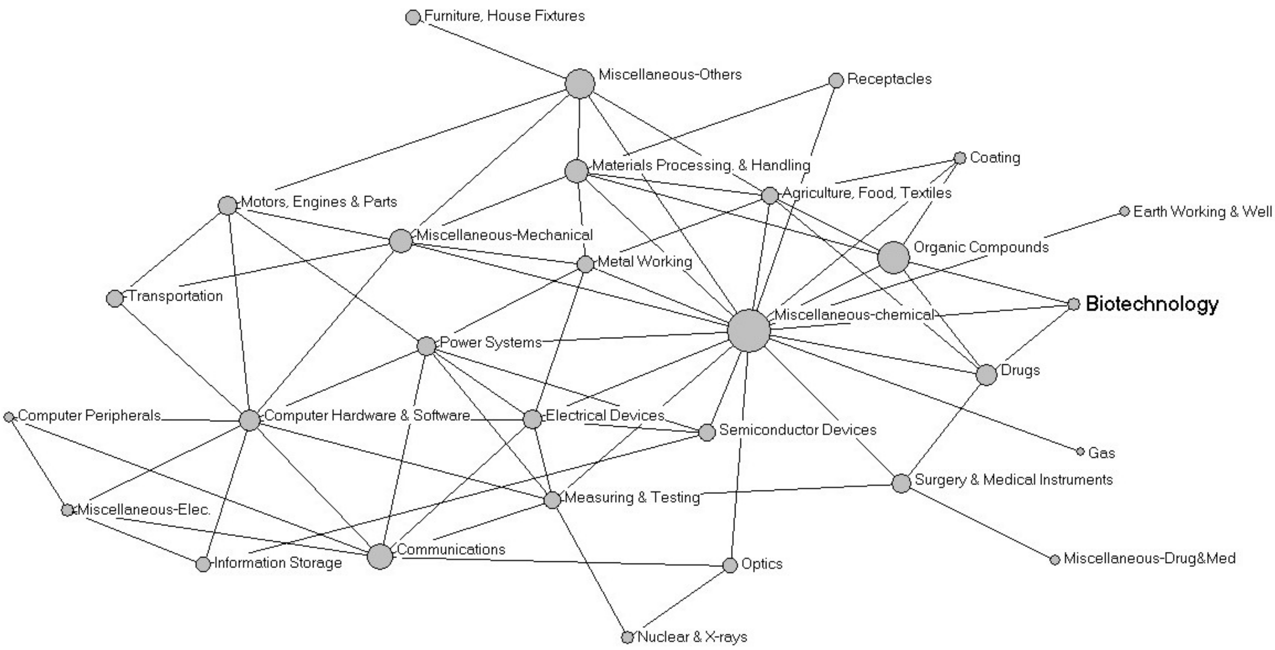

Figure 2.16 Plot of the core of the technological landscape of 1991-1995 (2000+ citations)

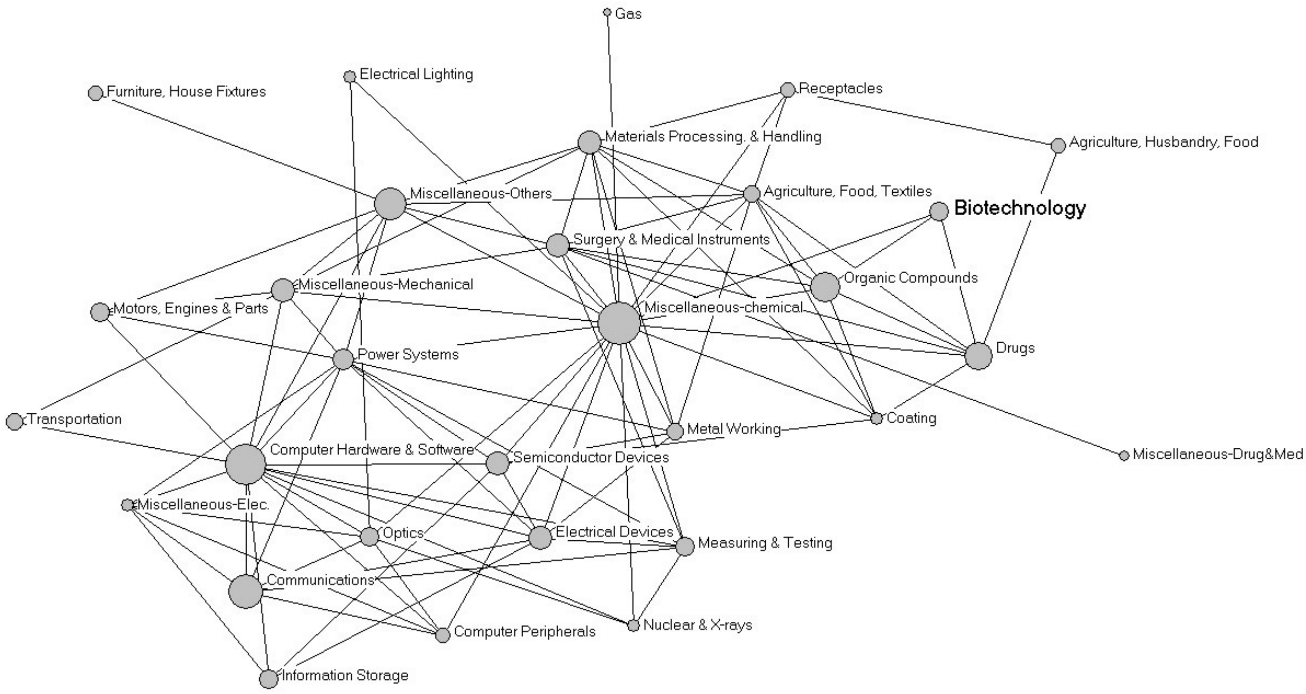

Figure 2.17 Plot of the core of the technological landscape of 1996-2000 (3000+ citations)

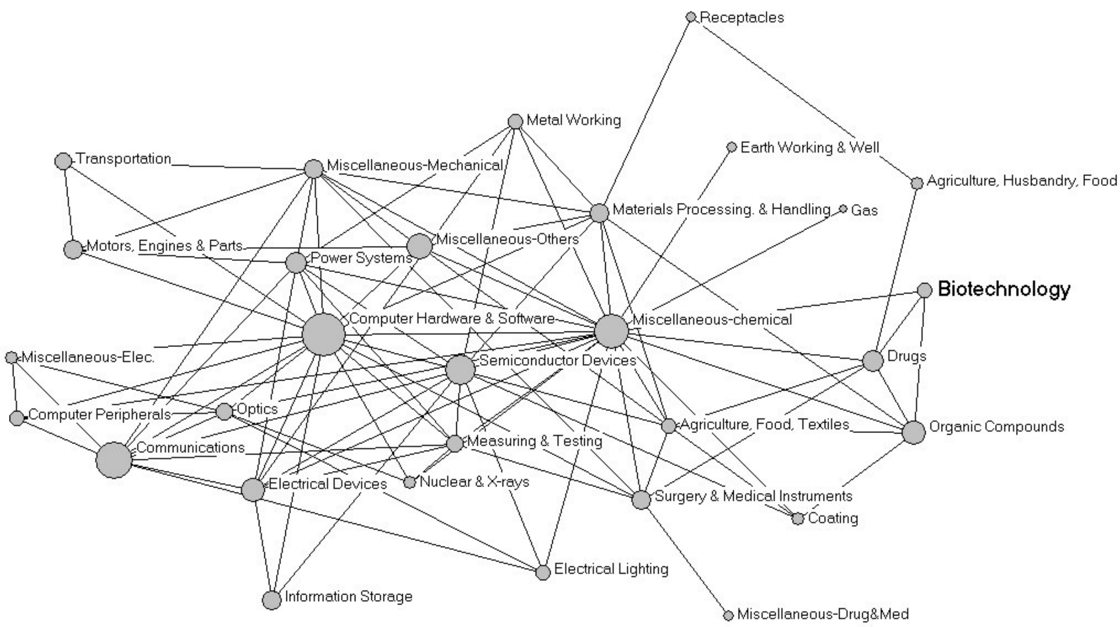

Figure 2.18 Plot of the core of the technological landscape of 2001-2005 (5000+ citations)

2.5 The future of biotechnology

It might have become clear from the previous discussion that biotechnology has many (potential) applications in a diverse array of domains. For example, in healthcare, biotechnology is argued to lead to predictive, preventive, and personalized medicine. More specifically, by studying a patient's genome or DNA, it is possible to determine his or her disposition to diseases, identify ways that prevent a disease from actually manifesting itself, and develop custom-made medications in the event that the disease does occur (BIO, 2008). In addition, understanding cell differentiation implies an ability to replace any part of the body, also referred to as regenerative medicine (van Santen, Khoe, & Vermeer, 2007). To give a non-healthcare example, in the agriculture industry, biotechnology can be used to increase yields by increasing stress tolerance levels of crops and animals (BIO, 2008). Closely related, in food technology, the quality of food can be increased by increasing the health and nutritional benefits of food, such as a pig that produces high levels of omega 3 fatty acids, or the so-called 'golden rice' that alleviates micronutrient deficiencies in developing countries (Paine et al., 2005). Moreover, there are also many industrial and environmental applications of biotechnology, such as, for example, organisms that increase efficiency of chemical processes, convert plant matter into biofuel, or remediate our natural environment (BIO, 2008). These are just a few of the many applications of biotechnology, and the possibilities are virtually endless. For example, some of the more distant and exotic examples are a space ship that assembles itself, a tree that grows separate rooms that can subsequently be used as a house (Endy, Thomas, & Brand, 2008), or the terraforming of Mars (Kuldell & Shetty, 2009). Even though the latter examples already stretch the imagination of most people, if there is something that history has taught us, it is that future developments will most likely even take us beyond our wildest imaginations.

It is not so much a question of whether but rather of when these applications will become solidified. Unmistakably, this is difficult to say and depends to a large extent on the priority that is given to and the amount of resources invested in the creation of general (e.g., stem cell research) and specific applications (e.g., the development of organisms that convert coal into methane). With respect to healthcare applications, we can make the following observations. According to the US Centers for Disease Control and Preventions (CDC), chronic diseases (such as cardiovascular disease, cancer, and diabetes) are among the most prevalent and costly of all health problems. To be specific, the direct (i.e., medical costs) and indirect (i.e., productivity losses) costs of diabetes are $174 billion a year, of arthritis $128 billion, cardiovascular disease $448 billion, obesity nearly $117 billion in 2000, and cancer an estimated $89 billion annually in direct medical costs in the US (CDC, 2009). Due to rising costs (especially of the obesity-related cardiovascular diseases) and the aging of society, it becomes clear that this problem cannot be resolved by controlling healthcare costs alone (Termeer, 2002). Hence, there exists a strong current to bring these costs down through innovative solutions enabled through biotechnology. For example, stem cells hold the key to curing diseases such as Parkinson's disease, diabetes, and cardiovascular disease (NIH, 2008).

At this moment, biotechnology is no more than a collection of technological components (BIO, 2008) that are highly complex and heterogeneous because human biology is a highly complex, highly integral system (Pisano, 2006). This means that biological processes posses a degree of integration of their parts that is far greater than that of non-living systems (Andrianantoandro, Basu, Karig, & Weiss, 2006), which results from the approximately 3.8 billion years that it has taken for nature to optimize its designs through evolution.[7] The genetic code or the machine language of the living world (i.e., DNA) is just yet discovered. Due to incomplete knowledge of biology (Andrianantoandro et al., 2006), biotechnology is fragmented into highly specialized separate fields, each with its own set of focal problems, languages, intellectual goals, theories, accepted methods, publication outlets, and criteria for evaluating research (Pisano, 2006). As these separate fields do not even share a common lexicon (Hood, 2004), communication is greatly hampered. Adding to this complexity is the fact the fields are still in development and therefore not stable (Endy, 2005; Pisano, 2006). Because biotechnology's components are still under development, the configuration of these components is highly unstable, which severely hampers developments. In other words, currently, no stable configuration or 'paradigm' exists for biotechnology (Endy, 2006), which implies the existence of many unknown unknowns (Knight, 1921) or strong

[7] The oldest ancient fossil microbe-like objects are dated to be 3.8 billion years old (Fedo, Whitehouse, Camber, 2006)

uncertainty (Dosi, 1988; Pisano, 2006). A stable configuration or 'paradigm' identifies the core components to be developed and the relationship between these components. The emergence of a stable configuration or paradigm is important because it (1) facilitates cumulative progress, (2) provides an 'architecture' that facilitates specialization and integration, and (3) structures ecological processes between (populations) of organizations (Dosi, 1988; Pisano, 2006). Hence, the way forward for biotechnology is in the creation of a paradigm, as this decreases uncertainty and enables cumulative changes through specialization. To determine the progress towards this goal, we turn to the domain of synthetic biology.

2.5.1 Synthetic biology

Within the domain of synthetic biology, complex systems are designed by (re-) combining DNA into biological parts that represent biological functions (Andrianantoandro et al., 2006). Building and modifying these biological parts essentially implies a transition from reading the genetic code to writing it (Post, 2008). The basic design units are the biological parts, and these are extremely important because the ability to quickly and reliably engineer is a function of the libraries of standard interchangeable parts (Canton, Labno, & Endy, 2008). Historically, a reductionist approach (i.e., analysis) has been applied, and very successfully so, to develop models of the workings of life (Endy et al., 2008). However, the proof of the putting is in its eating. This means that we only know whether these models are correct when actually putting these parts back together and see what happens. With analysis, if data contradict the theory, the data can be neglected (or even adapted) to safeguard the theory (Benner & Sismour, 2005). In contrast, within synthetic biology, if the data do not fit the theory, the biological parts or systems simply do not work, and there is absolutely no room for inconsistencies and ambiguities. As such, synthesis essentially drives the evolution of paradigms (Benner & Sismour, 2005), and is the place where the rubber meets the road.

> *"Synthesis defines an ambitious 'put-a-man-on-the-moon' goal. By doing so, it forces scientists and engineers to cross uncharted terrain in pursuit of the goal. This requires the solution of unscripted problems that are not normally encountered through either observation or analysis. Furthermore, the problems cannot be ignored if they contradict a paradigm. With analysis, if the data contradict the theory, the data are (as often as not) discarded to protect the theory. If one does this when putting an orbiter around Mars, however, the orbiter crashes" (Benner & Sismour, 2005: 534).*

So, how far are we from truly being able to perform synthetic biology? Essentially, the machine language is there, which are the genetic instructions encoded in DNA. This implies that synthetic biology relies heavily on two technologies, which are

DNA sequencing (i.e., reading DNA) and DNA synthesis (i.e., writing DNA). Regarding the sequencing of DNA, the National Human Genome Research Institute (a division of the US National Institutes of Health) has set the realistic target that by 2014, the entire human genome (i.e., a patient's complete DNA or approximately three billion base pairs) can be sequenced for approximately $1000 in a relatively short time frame (Bourzac, 2009).[8] With respect to DNA synthesis, the genome of Mycoplasma genitalium was recently synthesized, which consists of 582,970 base pairs (Gibson et al., 2008). This figure approximately doubles every 14 months (Endy et al., 2008), which would imply that the human genome can be fully synthesized around the year 2020. So, both the reading and writing of DNA shows a geometric increase that is comparable to the one that characterizes information technology, better known as Moore's law.

Even though the technological potential is surely there, this potential does not yet translate into product improvements or price reduction like they do in information technology. We can thus ask ourselves what is needed to translate this technological potential into concrete products and processes to unleash the economic and social value that lies hidden in biotechnology. What is needed is a stable configuration (e.g., of resources and skills) that makes it possible to effectively take advantage of this technological progress. Clearly, this is not an easy task as biotechnology is a highly complex technological domain. However, according to Endy (2005), the only reason that biotechnology is so complex is because we have never made it simple. To make it simple, he proposes to apply the design principles from engineering, which are abstraction, decoupling, and standardization (Canton et al., 2008). Abstraction is a powerful technology for managing complexity, and according to Endy (2005: 451), "[t]he purpose of an abstraction hierarchy is to hide information and manage complexity." He proposes four levels of abstraction, namely (1) DNA, (2) parts, (3) devices, and (4) systems, as in Figure 2.17. In this hierarchy, 'DNA' refers to the genetic material, 'parts' are basic biological functions (e.g., a DNA-binding protein), 'devices' are any combination of 'parts' that perform a human-defined function, and 'systems' are any combination of 'devices'. Abstraction barriers (indicated by the line between abstraction levels) block all exchange of information between levels, while interfaces (the 'gates' between abstraction levels) enable the limited and principled exchange of information between levels of abstraction. For this abstraction hierarchy to be useful, individuals must be able to work independently at each level of the hierarchy.

Decoupling means to separate a complex problem into simpler sub-problems that can be worked on independently, in such a way that the resulting work can eventually be combined into a functioning whole (Endy, 2005). The most obvious and basic decoupling within synthetic biology is to separate the design of DNA from the production (i.e., synthesis) of DNA. The ability to decouple DNA design from DNA

[8] In 2007, the costs of sequencing an entire human genome were still roughly $1 million.

production is driven by the advancements in DNA synthesis. Currently, biological researchers spend about 50 per cent of their time fabricating the genetic material to be used in their experiments (Endy, 2005). So, separating design from production would lead to a two-fold increase in research output. Finally, with respect to standardization, standards are highly important in our modern societies, underlying many aspects of our modern world. In the context of biotechnology, even though several useful standards have already arisen, there are still tremendous costs because of a lack of standards (Endy, 2005).

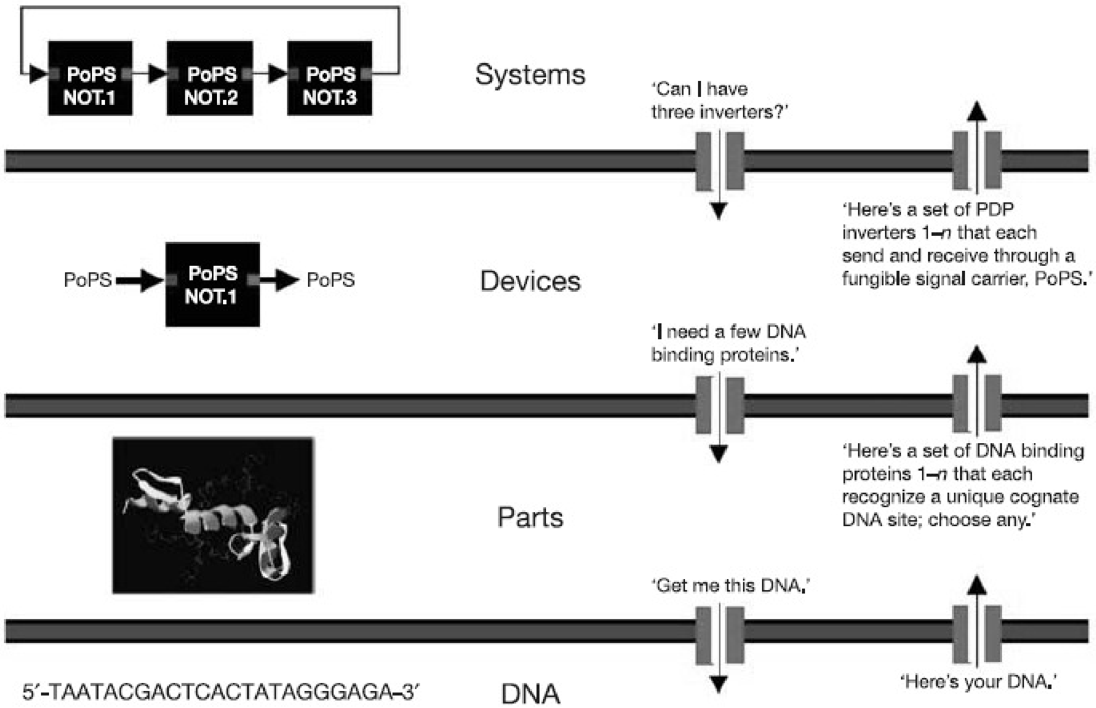

Figure 2.19 An abstraction hierarchy that supports the engineering of integrated genetic systems (source: Endy, 2005)

It goes without saying that the classical ideas of abstraction, decoupling, and standardization have to be adjusted to take into account the characteristics properties of biology (Andrianantoandro et al., 2006). However, viewed from an engineering perspective, parts are more suitable when they contribute independently to the whole (Benner & Sismour, 2005), also known as modularity (Henderson & Clark, 1990; Pisano, 2006). It thus makes sense to search for independently interchangeable parts, which is why synthetic biology is currently making an effort to create these independent parts (e.g., consider the Biobricks initiative at MIT) that can be effectively recombined into devices and systems that actually work. However, because biological parts are highly specialized and specific, this is not an easy task and entails a great deal of redesigning existing components. Ultimately, synthetic biology succeeds to the extent to which this independence approximation can be reached or created (Benner & Sismour, 2005). This independence would also facilitate a move of biotechnology from (university) labs to garages (Endy et al., 2008), also known as the do-it-yourself biotechnology or DIYBIO movement (Kuldell & Shetty, 2009), which is required to unleash the full creative potential of our society, much like the internet revolution several years ago.

Part II Technology

"Technology is a gift of God. After the gift of life it is perhaps the greatest of God's gifts. It is the mother of civilizations, of arts and of sciences."

~ *Freeman Dyson*

Chapter 3

The Ecology of Technology

3.1 Introduction

Nowadays, it is commonly known that technology plays an important role in the evolution of our modern-day society. After all, it is widely recognized that technology drives economic growth, and structures the relationships between individuals, groups, and organizations (Barnett, 1990; Duysters, 1995; Marx, 1906; Schumpeter, 1943; Tushman & Nelson, 1990). Technological change has mainly been studied from the perspective of evolutionary economics, which is based on Schumpeter's (1943) notion of technological change as an evolutionary process, as well as in the neoclassical tradition in economics, albeit less so. In the current chapter, we take a different route. Our key argument is that using insights from organizational ecology, a prominent sociological theory of the evolution of populations of organizations, will produce value added. We coin this new approach the 'ecology of technology'.

Although the Schumpeterian conception of technological change as an evolutionary process has been widely adopted in the literature, an in-depth understanding of what it precisely is (and does), is still argued to be in its infancy, at best (Fleming, 2001; Fleming & Sorenson, 2001). If so, this implies that a great challenge is to specify a really evolutionary process that explains how technological change comes about endogenously. The purpose of the current chapter is to move beyond a descriptive account of technological change, and to contribute to an explanation of the very nature of the growth pattern that is associated with endogenous technological change. To achieve this goal, as said, we will use notions from organizational ecology. In doing so, we will focus on the evolutionary – or ecological, for that matter – process of a technology's growth. In organizational ecology, the focus is on the evolution of a population of organizations. Adopting a similar logic, we deal with the evolution of a population of inventions. More specifically, by conceiving of technology as a system composed of a set of interdependent populations of related inventions (i.e., technological components), we aim to determine to what extent the pattern of technological growth can be attributed to the structural characteristics of technology. It is in this sense that our approach deals with endogenous growth of a technology.

In line with the work of Podolny and Stuart (1995), we claim that the notion of a technological niche offers a platform from which we can develop a deeper understanding and explanation of this process of endogenous technological growth. Accordingly, we define the niche at the level of a technological component (i.e., a population of related inventions), embedded within a technological system. As mentioned, our key aim is to develop a theory of why growth rates differ across technological components due to the structural characteristics of technology. As we will argue in greater detail below, this process of endogenous technological growth is determined by the 'ecological' characteristics of a technological component and the way in which this component is embedded in the technological system and the larger technological environment. This makes the concept of a technological niche useful for the purpose of our study as it points to the important role of the structural characteristics internal to the technology in driving the process of technological growth. Such a structural view on technological growth is ill-developed, to date, apart from a few notable exceptions that we will discuss in detail below (Fleming, 2001; Stuart, 1999).

Hence, the theoretical claim that this chapter makes is twofold. First and foremost, to come to a better understanding of the process of technological growth, we argue that a systemic perspective towards technology is warranted. That is, we perceive of a technological system as a set of interdependent components, which are embedded in the larger technological environment, commonly referred to as a technological landscape. In turn, this landscape can be conceived of as a population of technological systems. As a result, we can nicely bring in insights from organizational ecology, and produce value added. Second, these technological growth patterns are to a large extent determined by structural characteristics of technology (i.e., the characteristics of the technological environment in which the technology is embedded). After developing our theory, we will test specific hypotheses that follow from this ecological logic through an empirical analysis of patents and patent citations in biotechnology. Note that given our focus on patent data, we operationalize growth as entry (normally, growth is equated with net entry – i.e., entry minus exit), as patents do not exit.[9] Hence, in the remainder, technological growth and entry are used interchangeably

The major contribution of this chapter is, therefore, that we further our understanding of the process of endogenous technological growth by employing notions from organizational ecology, in developing a systemic perspective towards technology that may be coined the 'ecology of technology'. In doing so, we extend the notion of the technological niche by adding internal diversity as a key structural feature, and illustrate the importance of adding a measure of technological diversity in evolutionary and ecological models of technological growth. Moreover, by applying models from organizational ecology to technological populations, we demonstrate how these concepts can be applied empirically, here in the context of biotechnology.

[9] Even though the legal life span of a patent is approximately 20 years and the economic life span of most patents is considerably less, the technological life span of a patent can be much longer than 20 years. The reason is that technological development is cumulative, which means that future developments can build upon individual patented inventions long after its legal or economic life span.

The structure of this chapter is as follows. Section 3.2 describes the process of endogenous technological growth. We develop our theoretical model and associated hypotheses in Section 3.3. In Section 3.4, we elaborate on the empirical setting of our study, introduce our empirical measures, and explain our estimation methods. Section 3.5 presents the results of our empirical analyses. And finally, in Section 3.6, the findings are discussed in relation to our theory and the broader literature.

3.2 Endogenous technological growth

In the previous century, Schumpeter (1943) presented an evolutionary theory of the workings of the capitalist system, driven by forces of technological change. He conceived technological change (i.e., growth) as a process of recombination, where (existing) components are brought together in new ways (Schumpeter, 1939). Since then, the conception of technological growth as a process of recombination has been widely adopted in the literature (Basalla, 1988; Fleming, 2001; Fleming & Sorenson, 2001; Henderson & Clark, 1990; Nelson & Winter, 1982). In this chapter, we continue in this tradition and view invention as a process of recombination of components, where components refer to the constituents of invention (Fleming, 2001). This notion implies technological lineage, where an invention builds upon antecedent inventions, and can subsequently become the basis for future (descendant) inventions itself (see Figure 1.3).

Even though the notion of technological change as a process of recombination has been widely acknowledged, the precise workings hereof are rather ill-defined. This is mainly because a structural or systemic view is relatively underdeveloped, to date, apart from a few notable exceptions (Fleming, 2001; Stuart, 1999). In the current paper, our key aim is, therefore, to develop a theory of why growth rates differ across technologies due to the structural characteristics internal to technology itself. Our main claim is that, by viewing technologies as populations of related inventions, we can produce value added by bringing in insights from organizational ecology, a prominent sociological theory on the evolution of populations of organizations. More specifically, we view technology as a system that cuts across organizational boundaries (Barnett, 1990). In doing so, we basically focus on the aggregate pattern of development of all organizations that are active in a certain technological domain. Accordingly, we use Hawley's (1950) ecological framework and study technology in terms of its elemental systems or components. So, in analogy with Ruef (2000), we define a technological system as a bounded set of technological components with a related identity. In turn, a technological component is defined as a population of related technological inventions. In doing so, we effectively develop a multi-level model of technological growth (see Figure 3.1 below). Because the phenomenon of technological growth is inherently of a multi-level nature, we are able to add insight and depth well beyond any single level of analysis (Tushman & Nelson, 1990).

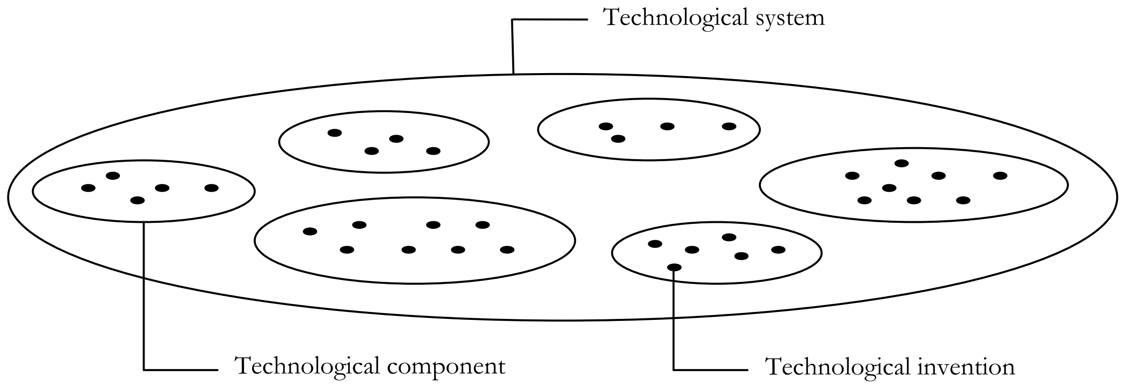

Figure 3.1 A multi-level model of technology

We study the entry of inventions into technological components, or the growth of component technologies. As can be seen in Figure 3.1, these components are embedded in a larger technological system (e.g., biotechnology), and are composed of populations of related inventions. In line with the work of Podolny and Stuart (1995), we claim that the notion of a technological niche offers a platform from which we can develop a deeper understanding and explanation of this process of endogenous technological growth.

3.3 The technological niche

The concept of the niche was first developed by Charles Elton (1927), and is still central to many ecological studies today, where it is used to delineate the relational position of an organism, population or species in an ecosystem. The niche has received widespread attention in numerous empirical studies (Baum & Singh, 1994b; Dobrev, Kim, & Carroll, 2002b; Dobrev et al., 2003; Dobrev et al., 2001b; Freeman & Hannan, 1983; Hannan, Carroll, & Polos, 2003a; Lawless & Anderson, 1996; Podolny & Stuart, 1995; Podolny et al., 1996), as well as in theoretical work (Hannan et al., 2003a; Hannan et al., 2007; Peli, 1997; Peli & Nooteboom, 1999; van Witteloostuijn & Boone, 2006). Here, we claim that building upon this wealth of research is fruitful to elucidate the process of the entry of inventions into our technological components.

The technological niche was first developed by Podolny and Stuart (1995) to investigate the effects of crowding and status for the future importance of individual inventions. They defined the technological niche as the relational context of an invention that co-evolves with technological change. Podolny, Stuart, and Hannan (1996) subsequently applied the concept of the technological niche at the organizational level of analysis, to study the effects of crowding and status on organizational growth and survival. In this study, we want to continue in this tradition, and build on this notion of the technological niche. However, instead of applying the niche to individual inventions or to organizations, we define the niche at the level of a technological component. That is, we define the technological niche as the relational context of a technological component (e.g., genetic engineering), embedded within a technological system (e.g., biotechnology). To reiterate, we are thus investigating the aggregate pattern of development by all organizations active within a certain technological component or system. Our key dependent variable is growth of the technological component as reflected in entry by new inventions, coined component growth.

According to Podolny and Stuart (1995), the growth of technological niches (or niche entry) mainly depends on three attributes, which are: (1) the characteristics of the technological component niche itself, (2) the embeddedness of the component niche in the technological system or landscape (i.e., the broader technological environment), and (3) the characteristics of the organizations populating the technological component niche. As argued, the aim of this study is to develop a model of endogenous technological change. We therefore choose to abstract from the organization, and mainly focus our attention on attributes (1) and (2). Below, we will subsequently discuss the dimensions of the niche central to our theory, focusing on both its internal (i.e., niche density and diversity) and external (i.e., crowding and status) features. Note that, given our application to component niches of biotechnology (see below for details), we often refer to the short-cut component or niche for component niche.

3.3.1 Component density

Researchers have observed a characteristic pattern of evolution of diverse organizational populations: initially, after a slow kick-off, population size increases rapidly, and then stabilizes or even declines in numbers (Carroll, 1984; Carroll & Hannan, 1989a; Carroll & Hannan, 2000; Hannan & Freeman, 1989). Intrigued by the universality of this typical S-curved pattern, organizational ecologists have sought to explain this phenomenon. They were able to do so by integrating elements from ecological and institutional theories, into what is known as density dependence theory (Carroll & Hannan, 1989a). This theory posits that the two general forces of selection – i.e., social legitimation and diffuse competition – are linked to the density of organizational populations (Carroll & Hannan, 2000). Basically, population density serves as a surrogate for the difficult-to-observe features of the material and social environment that affect organizational founding and mortality rates, particularly competition and legitimation (Hannan & Freeman, 1989).
Legitimation refers to "the standing as a taken-for-granted element in a social structure" (Hannan et al., 2007: 78), and is especially important in the early stages of population development. After all, the capacity of an organizational form to mobilize resources is to a large extent dependent on the extent to which (extremely skeptical) resource controllers take the form for granted (Aldrich & Fiol, 1994; Carroll & Hannan, 2000). Legitimation is tied to density because, according to Hannan and Freeman (1987: 918), "if institutionalization means that certain forms assume a taken-for-granted character, then

simple prevalence of the form ought to legitimate it." Legitimation processes thus produce a positive relationship between population density and founding rates.
Density also has an obvious link with diffuse competition, which is defined as common dependence on the same resource pool. After all, if density increases linearly, the number of potential competitive links increases exponentially (Carroll & Hannan, 2000). This implies that density increases diffuse competition at an increasing rate, as more organizations fight for limited resources, resulting in declining founding rates and increasing mortality rates (Hannan & Freeman, 1987). The joint forces of legitimation (dominant at low density) and competition (dominant at high density) produce non-monotonic density-dependent processes of organizational entry (reverse U-shaped) and exit (U-shaped), which together generate an S-shaped growth curve of population density.

Even though the theory of density dependence has been primarily applied to organizational populations, and very successfully so, recent research illustrates that, due to its general nature, this argument can also be effectively applied in other settings, such as the birth and death rates of national laws (de Jong & van Witteloostuijn, 2008; van Witteloostuijn, 2003; van Witteloostuijn & de Jong, 2009; van Witteloostuijn & Jong, 2007) and organizational rules (March et al., 2000; Schulz, 1998). As such, we believe that density dependence logic can also fruitfully be used in the study of evolutionary processes within technological populations (cf. Pistorius & Utterback, 1997). After all, technology also displays characteristic patterns of growth (Dosi, 1988), and the S-shaped growth or logistics curve is also extensively documented for technology (Andersen, 1999; Griliches, 1957; Mansfield, 1961; Rogers, 1962; Young, 1993). However, we have to keep in mind that, even though similarities between technologies and organizations provide a useful platform for applying analytical concepts from one domain to the other, we have to be careful not to equate one sphere with the other (Pistorius & Utterback, 1997). This implies that we should carefully consider the extent to which processes of competition and legitimation operate in technological populations.

It is widely acknowledged that technologies need to be legitimized (Aldrich & Fiol, 1994; Anderson & Tushman, 1990; Dosi, 1988; Duysters, 1995; Nooteboom, 2000; Zucker, 1989). According to DiMaggio and Powell (1983), organizations even adopt technology to enhance their own legitimacy. Hence, technologies are institutionalized and become a taken-for-granted means to accomplish organizational ends (Meyer & Rowan, 1977). This process of legitimation is especially important in the formative stage of a technology (i.e., a technological component) when, akin to the initial stages of organizational populations, "important constituents, such as investors, founders, potential customers and employees lack a clear understanding of the newly emerging activity, hampering taken-for-grantedness and resource mobilization" (Bogaert, Boone, & Carroll, 2007: 3). Here, we believe that the denser the component's technology (i.e., the more technological inventions there are in the component's niche), the better understood the technological component is, and the more it is taken-for-granted as the appropriate means to accomplish a certain goal (e.g., use rDNA technology to modify the genetic structure of living material). Obviously, this process enhances the growth of the technological component. So, analogous to the acceptance of a new organizational form by society, legitimacy of a new technological component increases with the number of technological inventions in the component's niche. Hence, at low levels of component density, we expect to find a positive association between component density and component entry.

Ideas and innovations compete with one another for the attraction of resources and attention (Basalla, 1988; Podolny & Stuart, 1995). That is, due to the scarcity of stakeholder resources, only a limited amount of resources and attention can be attributed to (a particular kind of) technological development at a certain point in time. Because a firm's research budget or an investor's capital is limited, alternative inventions compete for these scarce resources. Increasing density increases the number of inventions that depend upon these scarce resources for further development (e.g., successful introduction into the market; i.e., turning the invention into an innovation). So, when these resources become scarce (i.e., at high levels of component density), processes of competition start to develop between alternative inventions. Hence, at high levels of component density, we expect a negative association between component density and component entry. Our first hypothesis hence becomes

Hypothesis 3.1: *Component density is first positively and later negatively associated with component growth, implying a non-monotonic inverted U-shaped effect of component density on component growth.*

3.3.2 System density

Over the years, density dependence theory has received considerable critique. This is mainly the result of the generality of the model. On the one hand, regarding the legitimation processes, opponents – mainly institutionalists – argue that legitimation is a multi-dimensional construct that cannot be adequately represented by a measure as crude as population density (Baum & Powell, 1995; Zucker, 1989). This critique argues that population evolution is highly dependent on idiosyncratic events (e.g., legislative changes, overt political support, and entrepreneurial initiatives) that are largely ignored when merely studying population numbers. Accordingly, ecologists argue that those events are indeed important, but can never be fully taken into account by any general theory, and therefore opt to control for such events instead (Carroll & Hannan, 1989b). As mentioned, it is our aim to develop a theory that allows for a systematic investigation of technological growth (and, in a later stage, technological evolution), and we therefore choose to follow the ecological approach in this matter by controlling for specific events.

On the other hand, the competitive aspect of the theory has also been challenged. It is argued that populations are not fully homogeneous and that segments of the population respond differently to (mainly) competitive processes (Baum & Shipilov, 2006; Lomi, 1995). Indeed, recent research indicates that competitive processes are highly localized because competition is tied to material resources (i.e., plants, products, and people), and is therefore hampered by spatial and geographic boundaries (Baum & Shipilov, 2006; Carroll & Hannan, 2000; Lomi, 1995). In contrast, legitimation processes are tied to information, which flows more freely, and is therefore hampered less by boundaries. Accordingly, legitimation processes are argued to operate more broadly than competitive processes (Carroll & Hannan, 2000). This provides fertile ground for extending the original density dependence model.

One of the proposed extensions is to employ multi-level models, where processes of legitimation are allowed to operate more broadly than competitive processes (Hannan, Dundon, Carroll, & Torres, 1995). Here, we follow this line of reasoning and argue that the flow of material resources (i.e., plants, products, and people) is not only disrupted by political and physical barriers (Carroll & Hannan, 2000), but also by technological boundaries. That is, we claim that technology also localizes competitive processes, whilst processes of legitimation operate on a broader technological scale. Hence, we expect density within the entire technological system to be tied to processes of legitimation (and not to competition). If this would not be the case, it would imply that the set of technological components does not really comprise a coherent technological system. After all, a set of components comprise a system only when these components form an integrated whole – that is, when the whole is greater than the sum of its parts. In other words, processes of legitimation at the system level imply that the components are interdependent. Our next hypothesis is thus

Hypothesis 3.2: *System density is positively associated with component growth.*

3.3.3 Component diversity

As previously noted, density dependence theory has been criticized because it assumes that populations are homogeneous while recent research finds that population segments respond differently to processes of competition and legitimation. When investigating these processes within a population, it thus becomes important to consider whether the population is subdivided into segments (i.e., whether populations are homogeneous or diverse). In the context of our current study, three motives come to mind for considering diversity. First, according to Durkheim (1933), there is an inverse relationship between diversification (i.e., diversity) and competition. That is, if a population becomes more diverse, the level of competitive intensity within the population decreases. So, according to this argument, as the rate of entry is tied to the competitive intensity within a technological component, we expect component entry to increase with component diversity. Second, diversity mitigates lock-in and provides flexibility in uncertain environments (Stirling, 2007). Because technological development within biotechnology is of a highly uncertain nature, flexibility is important by providing alternative directions for future development. In this sense, diversity is indicative of niche width, and increasing the diversity of the niche increases its potential applicability in the wider environment, implying that it is appealing to a greater variety of stakeholders, which positively affects the rate of component entry. Third, and finally, technological change is a process of recombination (Schumpeter, 1939), so increasing the number of subcomponents (in a component) increases the opportunities for their (re)combination, yielding further opportunities for new combinations. Hence, we expect diversity to have a positive effect on component entry because it (1) reduces competition, (2) mitigates lock-in by increasing flexibility, and (3) increases recombinatory potential. We thus have

Hypothesis 3.3: *Component diversity is positively associated with component growth.*

3.3.4 Component status

Under component density, we have argued that processes of legitimation are tied to the occurrences of the componen's inventions. Moreover, we have also argued that processes of legitimation are present at the system level under system density. Even though we do believe that processes of legitimation at the system level affect all components within the system, it is highly unlikely that system-level legitimation will affect all components equally. Furthermore, we also do not believe that component density is a proxy that accurately describes the distribution of system-level legitimation among components. After all, component (or population) density is not a panacea to all legitimation-related questions. This means that we need another way to distinguish between the legitimation of individual components relative to the other components within the technological system. A well-known construct that measures legitimation at the individual member level is status, which is defined as a focal member's 'perceived' quality in relation to the 'perceived' quality of other population members (Podolny, 1993; Shrum & Wuthnow, 1988).

As such, status is an instance of endogenous system or population structuring that results from the interactions among members in a population. Akin to the importance of legitimation in the formative (or uncertain) stages of population development, status is mainly used by resource controllers to guide their decisions in uncertain environments. Due to the uncertainty, the quality of population members cannot be objectively determined. And, as a result, resource controllers rely on status to guide their decisions (Merton, 1968a; Shrum & Wuthnow, 1988). In the context of technological development, the role of status has been studied by Podolny and Stuart (1995) and Podolny, Stuart, and Hannan (1996).

According to these studies, as the uncertain environment makes quality perceptions dependent on status, status becomes important in guiding the flow of resources in technological developments. More specifically, as other organizations build upon the focal organization's technology, a certain legitimacy or status is conferred to that focal organization's technology (Podolny & Stuart, 1995). Here, akin to the explanation at the organizational level, we argue that, when aggregate technological developments build upon a focal technological component, a certain legitimacy or status is transferred to the focal component as it provides a signal to the stakeholders of the technological system that the focal component is worthy of attention and resources. This logic is visualized in Figure 3.2.

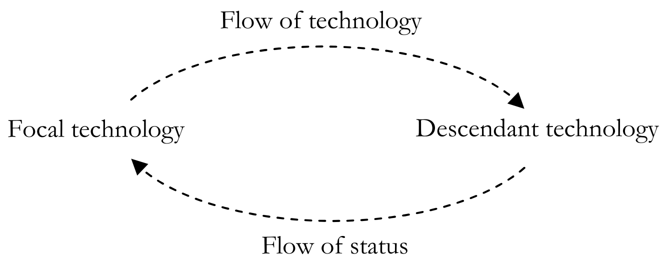

Figure 3.2 The flow of technology and status in technological development

So, in times of uncertainty, high-status components offer an anchor for technological investment (i.e., resources), attracting component entry. Podolny, Stuart, and Hannan (1996: 669) refrain from hypothesizing about the main effect of status because, as they argue, "one cannot specify an average status effect independent of a meaningful assessment of the average crowding or uncertainty in a technological domain." However, because technological developments within biotechnology can be characterized by high levels of average uncertainty (Pisano, 2006; Podolny et al., 1996), we expect status to have a positive main effect on component entry. Hence, we have

Hypothesis 3.4*: Component status is positively associated with component growth.*

3.3.5 Component crowding

In ecological studies, niche crowding or overlap is usually equated with competition, as it implies a similarity in resource requirements (Baum & Mezias, 1992; Dobrev et al., 2001b; Hannan & Freeman, 1977, 1989; Hannan et al., 2007; Podolny et al., 1996), and builds upon the notion that the potential for competition is directly proportional to the overlap of resource bases (Baum & Singh, 1994b). Here, we explore the extent to which we can apply these arguments to our setting. This means that we first need to define the resource base of our technological components. We claim that the resource base of our technological components can be properly represented by the knowledge base on which organizations build to generate the inventions within the component. After all, especially when markets are not (yet) existent, technological development is to a large extent dependent on the underlying knowledge base (Duysters, 1995).

Because inventions recombine technology from antecedent inventions, these antecedent inventions actually constitute the building blocks of these focal inventions. And, the uniqueness of the invention's building blocks determines the uniqueness of the invention itself (Fleming, 2001). Aggregated to the component level, this means that the more that a focal technological component builds upon unique elements, the more unique the focal component itself is. So, we define the technological antecedents of our focal technological components as its knowledge and resource base, and claim that an overlap in technological antecedents increases the competition experienced by the component, because it decreases the uniqueness of the technological component. Consequently, we argue that competition not only occurs within a technological component (as argued under component density), but also between technological components.

However, according to the extant literature, niche crowding can also contribute in a positive way to niche entry or growth, due to reputation and knowledge spillovers (Fleming & Sorenson, 2004; Jaffe, 1986; Levin, 1988), economies of standardization through a sharing of infrastructure (Baum & Haveman, 1997; Wade, 1995), and vicarious learning (Delacroix & Rao, 1994). This mutualistic relationship has been validated empirically in numerous studies (cf. Boone et al., 2004; Fleming, 2001; Jaffe, 1986; Levin, 1988; Pontikes, 2007; Spence, 1984; Stuart, 1999). Here, we explore the extent which these arguments can also be applied in a purely technological setting (i.e., when looking at aggregate patterns of technological development). First, reputation spillovers are obviously related to the process of legitimation. As argued, technology can become a taken-for-granted means to accomplish an organizational objective, implying the existence of legitimation or reputation spillovers from (the use of) one technology to the (use of the) other. Furthermore, knowledge spillovers within technological development are also well-documented. This has a rather logical explanation. That is, as the usage of technology increases, the documentation of technology also increases – for example, in patent documents, manuals, and books. As a result, the characteristics and behavior of often used technologies are better known. Second, economies of standardization or infrastructure sharing relate to the costs of transportation, communication, and ease of supply (Baum & Haveman, 1997), which are also important in the case of technological development. Consider, for example, the use of active compounds (e.g., molecules and proteins) in biological tests. Reliance on compounds that are not readily available obviously hampers technological development. Moreover, according to Pistorius and Utterback (1997), an emerging technology can benefit from the infrastructure that was created to accommodate the mature technology. Third, and finally, vicarious learning is possible through adaptation and avoidance of ideas, structures, and technologies (Delacroix & Rao, 1994), and by definition plays an important role in technological development. Accordingly, we also need to accommodate for a positive effect of component crowding on component growth.

Now, a question that remains is: How can we accommodate for both a positive and negative effect of component crowding? As mentioned, according to organizational ecology logic, processes of competition are more localized than processes of legitimation. After all, more local or more similar organizations are more likely to vie for the same pool of resources (Barnett, 1997). In a similar vein, we argue that more local technological components compete for the same resources, such as venture capital, investments, and research budgets. That is, we claim that competitive processes are bound by technological systems. This means that we distinguish between two forms of crowing. On the one hand, local crowding refers to crowding of our focal components amongst themselves (i.e., crowding within our technological system). On the other hand, global crowding refers to crowding of our focal component by non-focal components (i.e., crowding of our focal components by components from other technological systems, so non-biotechnology). This is visualized in Figure 3.3.

So, on the basis of the localized competition hypothesis, we expect that local (or within-system) crowding is mainly tied to competitive processes and global (or between-system) crowding is mainly tied to processes of legitimation. Our next pair hypotheses can now be formulated as

Hypothesis 3.5: *Local crowding is negatively associated with component entry.*
Hypothesis 3.6: *Global crowding is positively associated with component entry.*

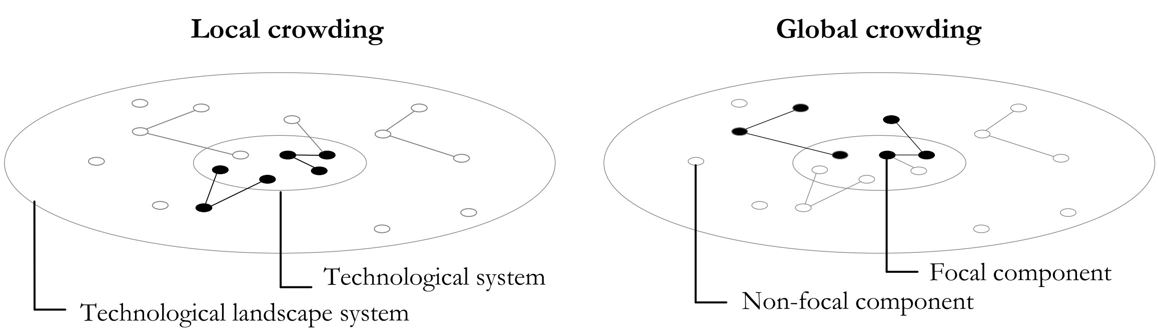

Figure 3.3 Local versus global crowding (black nodes indicate the different forms of crowding)

We have argued under component status that a certain amount of legitimacy is transferred to a focal organization when another organization builds upon the focal organization's technology. However, according to Podolny, Stuart, and Hannan (1996), such a technological tie between two organizations also implies that their technologies are similar, which increases the potential for competition between the two organizations. The authors reason that these technological ties have the most potent competitive impact in crowded regions of the network, resulting in clique-like structures among structurally equivalent organizations. They therefore claim that the effect of status is positive in uncrowded niches, and that this positive effect decreases with niche crowding. Similarly, we expect that these technological ties can also have competitive implications in our setting. However, because competitive processes are bound by technological systems, the effect of status only decreases with local crowding, and not with global crowding. This gives

***Hypothesis 3.7a**: The interaction term of local crowding and component status is negatively associated with component growth.*

***Hypothesis 3.7b**: The interaction term of global crowding and component status is not negatively associated with component growth.*

3.4 Methodology

Patents and patent citations provide the core of the data that we will use to test our hypotheses. Patents and patent citations have been used extensively in the study of technological change and organizational innovation (Fleming, 2001; Fleming & Sorenson, 2004; Podolny & Stuart, 1995; Sorensen & Stuart, 2000; Stuart, 1998; Stuart, 2000). Especially within biotechnology, patents form a reliable indicator of technological developments (Orsenigo, Pammolli, & Riccaboni, 2001; Powell, Koput, & Smith-Doerr, 1996), as all landmark innovations have been patented. Previous research has illustrated that the US patent system offers the most complete dataset for technological analysis, since the US is the world's largest and most international marketplace (Podolny & Stuart, 1995). Furthermore, because the US is a large and central market for biotechnology, it is standard practice of biotechnology companies from outside the US to patent in this country (Albert, Avery, Narin, & McAllister, 1991). We therefore use patent data from the United States Patent and Trademark Office (USPTO) in our empirical analysis.

Patents are classified by the USPTO following a hierarchical classification system, known as the United States Patent Classification System (USPC), which is divided into 375 main classes that jointly contain about 125,000 sub-classes. For a patent to be granted, the applicant must establish the novelty of the invention relative to all previous inventions. This novelty claim is established by identifying and citing what is referred to as "prior art". These citations are usually supplemented during the review by the patent examiner (Fleming, 2001). Previous research has clearly demonstrated the importance of patent citations (Fleming, 2001; Hall, Jaffe, & Trajtenberg, 2001a; Jaffe, Trajtenberg, &

Fogarty, 2000; Lanjouw & Schankeman, 2004; Lanjouw & Schankerman, 1999; Trajtenberg, 1990). We therefore use these citations to delineate technological lineage and the embeddedness of a focal technological component in the broader technological environment.

Table 3.1 Biotechnology's technological component niches

Niche	Subclass	Subclass description
435001	435001100	Differentiated tissue or organ other than blood, per se, or differentiated tissue or organ maintaining
435002	435002000	Maintaining blood or sperm in a physiologically active state or compositions thereof or therefor or methods of in vitro blood cell separation or treatment
435003	435003000	Condition responsive control process
435004	435004000	Measuring or testing process involving enzymes or micro-organisms
435005	435041000	Micro-organism, tissue cell culture or enzyme using process to synthesize a desired chemical compound or composition
435006	435440000	Process of mutation, cell fusion, or genetic modification
435007	435173100	Treatment of micro-organisms or enzymes with electrical or wave energy (e.g., magnetism, sonic waves, etc.)
435008	435174000	Carrier-bound or immobilized enzyme or microbial cell
435009	435183000	Enzyme (e.g., ligases (6.), etc.), proenzyme
435010	435235100	Virus or bacteriophage, except for viral vector or bacteriophage vector
435011	435325000	Animal cell, per se (e.g., cell lines, etc.)
435012	435410000	Plant cell or cell line, per se (e.g., transgenic, mutant, etc.)
435013	435242000	Spore forming or isolating process
435014	435243000	Micro-organism, per se (e.g., protozoa, etc.)
435015	435320100	Vector, per se (e.g., plasmid, hybrid plasmid, cosmid, viral vector, bacteriophage vector, etc.) bacteriophage vector, etc.)
435016	435262000	Process of utilizing an enzyme or micro-organism to destroy hazardous or toxic waste, liberate, separate, or purify a preexisting compound or composition therefore
435017	435283100	Apparatus
435108	435317100	Miscellaneous (e.g., subcellular parts of micro-organisms, etc.)
800001	800003000	Method of using a transgenic nonhuman animal in an in vivo test method (e.g., drug efficacy tests, etc.)
800002	800004000	Method of using a transgenic nonhuman animal to manufacture a protein which is then to be isolated or extracted
800003	800008000	Nonhuman animal
800004	800021000	Method of making a transgenic nonhuman animal
800005	800260000	Method of using a plant or plant part in a breeding process which includes a step of sexual hybridization
800006	800276000	Method of chemically, radiologically, or spontaneously mutating a plant or plant part without inserting foreign genetic material therein
800007	800277000	Method of producing a plant or plant part using somatic cell fusion (e.g., protoplast fusion, etc.)
800008	800278000	Method of introducing a polynucleotide molecule into or rearrangement of genetic material within a plant or plant part
800009	800295000	Plant, seedling, plant seed, or plant part, per se

Biotechnology patents are registered in classes 435 and 800 of the USPC. The domain of biotechnology has an average of 57 per cent of self-citations, and can therefore be considered as highly autonomous and independent. As such, biotechnology offers a setting suitable for an empirical investigation of the kind proposed here. The biotechnology domain contains 27 main sub-classes (18 in class 435 Molecular and Microbiology, and 9 in class 800 Multicellular living organisms and unmodified parts thereof and related processes), which are listed in Table 3.1. As argued, we define our technological niches (i.e., components) at this level of analysis.

3.4.1 Measures

Component growth, our dependent variable, is measured by the count of the number of patents that enter our focal components in a particular month in the period between 1976 and 2003. As we have repeated observations for the same components, our data actually form a time-series – cross-sectional panel. This panel is unbalanced, though, as not all components were in existence at the start of our time window.

Focal Component density or is a count of the total number of patents (divided by 1000) in the focal component in the month prior to the date of measurement of our dependent variable. So, this measure represents the stock of patents contained in the focal component.

System density is a count of the total number of patents (divided by 1000) within the domain of biotechnology (i.e., USPTO class 435 and 800) in the month prior to the date of measurement of our dependent variable. To avoid double counting, we subtract focal component density from system density.

Component crowding refers to the extent to which our focal components have an overlap with other components. First of all, to provide for a baseline model to test our hypotheses regarding the distinction between local and global crowding, we calculate the aggregate measure of crowding (i.e., Total crowding). For this measure, we use the following formula:

$$(3.1) \qquad CC_{it} = \sum_{j=1,\, j\neq i}^{j=J} \sum_{k=1, k\neq i, k\neq j}^{k=K} \frac{\left|A_{ikt} \cap A_{jkt}\right|}{\left|A_{ikt}\right|}$$

where CC_{it} refers to the crowding of component i at time t, A_{ikt} to the set of technological antecedents of component i that come from component k at time t, A_{jkt} to the set of technological antecedents of component j that come from component k at time t, $|.|$ to the cardinality of a set (i.e., the number of unique elements contained within the set), $\cap$ to the intersection of two sets (i.e., the common elements in both sets), and both J and K to the set of all components, so both focal and non-focal components. To make the number of non-focal components manageable, we have defined the non-focal components at the class level instead of at the main sub-class level.[10]

As mentioned before, we distinguish between local and global crowding to disentangle the processes of competition and legitimation that are associated with crowding. In our measure of Local crowding, we calculate the overlap of our focal

[10] Strictly speaking, this implies that our non-focal components are actually composed of alternative technological systems (i.e., non-biotechnology). However, we exclude this from our main text to reduce the complexity of our arguments.

components using (3.1). However, in this case, J refers to the set of focal component only, while K refers to the set of both focal and non-focal components. In our measure of Global crowding, we measure the overlap of our focal components with the non-focal technological components. To calculate this measure, we again use (3.1), but now J refers to the set of all non-focal components, whilst K refers to the set of all components (so both focal and non-focal).

Focal Component status is measured on the basis of patent citations. Patent citations reveal system-wide perceptions of the relative importance of patented technologies (Trajtenberg, 1990), and can therefore be used to measure the status of the component. Niche status is measured by the number of citations received by the technological component in the previous twelve months. In line with Podolny and Stuart (Podolny & Stuart, 1995), we use a ratio for component status to correct for the expanding risk set of patents in our components. The number of patent citations that a component receives is to a large extent dependent upon the number of inventions that are contained within the component (i.e., component density). So, therefore, we divide the number of patent citations by the density of the component. This also significantly reduces the correlation between, on the one hand, component status, and, on the other hand, component density and organizational density, reducing potential problems of multicollinearity. This implies

$$S_{it} = \frac{\sum_{j=1}^{J} CR_{ijt}}{\sum_{k=1}^{k=K} D_{it}} \qquad (3.2)$$

where S_{it} is the status of component i at time t, CR_{ijt} is the number of citations received by invention j in component i at time t, D_{it} is the density of component i at time t, and t refers to the 12 months prior to the month of observation of our dependent variable. Note that self-citations are excluded, as these does not adequately reflect the public deference process that this variable is supposed to represent (Podolny et al., 1996).

Focal Component diversity is measured via the distribution of patents across sub-components (or population segments) contained in the focal component over the previous twelve months. These sub-components are represented by the USPC sub-classes that are associated with the focal component. To measure component diversity, we will use Shannon's (1948) diversity measure, which is specified as

$$CD_{it} = \sum_{j=1}^{j=J} P_{ijt} \ln(1/P_{ijt}) \qquad (3.3)$$

where CD_{it} refers to the diversity of component i at time t, P_{ijt} is the share of patents in sub-component j at time t in component i, J refers to the total number of sub-components, and t refers to the 12 months prior to the month of observation of our dependent variable.

Our first control variable is Organizational density, which is a count of the number of organizations (in thousands) active in the technological component in the 12 months prior to the month of observation of our dependent variable. We expect a positive effect of organizational density on component growth. After all, the legitimation of technology is to a large extent determined by the number of organizations that adopt the technology (Duysters, 1995). Initially, increasing the number of organizations increases the rate of scientific discovery. However, at some point, increasing the number of organizations means that the chances for discovery decrease. Under these circumstances, the best defense or strategy for the organization is to control as much pieces of technology (Stuart, 1999), as these can be used as leverage (i.e., bargaining power) in the competitive arena. This leads to ineffective strategies of technological development, hereby depressing the technology's growth. Hence, we expect to find an inverted U-shaped effect of organizational density on component growth.

Table 3.2 Descriptive statistics of patent entry into biotechnology's components

Niche	n	mean	SD	variance	min	max	dispersion
435001	336	0.61	0.93	0.87	0	5	1.42
435002	336	0.86	1.14	1.30	0	6	1.51
435003	336	0.14	0.36	0.13	0	2	0.95
435004	336	44.15	43.60	1901.21	1	217	43.06
435005	336	26.58	21.00	440.94	1	113	16.59
435006	336	2.49	3.50	12.28	0	16	4.94
435007	336	0.41	0.74	0.55	0	3	1.34
435008	336	1.71	1.43	2.06	0	7	1.20
435009	336	9.08	8.43	71.10	0	45	7.83
435010	336	1.31	1.71	2.92	0	9	2.22
435011	336	6.68	8.23	67.81	0	37	10.15
435012	336	0.87	1.21	1.45	0	7	1.68
435013	336	0.04	0.22	0.05	0	2	1.30
435014	336	5.74	4.51	20.36	0	21	3.54
435015	243	3.00	3.41	11.65	0	24	3.89
435016	336	2.74	2.73	7.46	0	14	2.73
435017	336	5.20	4.19	17.56	0	25	3.38
435018	336	0.04	0.21	0.04	0	1	0.96
800001	121	0.66	0.89	0.79	0	4	1.20
800002	159	0.24	0.52	0.27	0	2	1.14
800003	177	1.53	1.92	3.71	0	10	2.43
800004	203	0.32	0.63	0.40	0	3	1.24
800005	336	1.27	2.76	7.61	0	21	5.97
800006	225	0.06	0.23	0.05	0	1	0.95
800007	336	0.02	0.16	0.03	0	2	1.27
800008	200	4.11	4.61	21.27	0	21	5.18
800009	336	3.94	7.03	49.43	0	31	12.53

Legend: n = number of observations; SD = standard deviation; min = minimum; max = maximum; dispersion = variance/mean.

We also include Year dummies in all our analyses to control for year-specific effects. Furthermore, in accordance with prior research, we also add the number of previous entries and its square – Previous entry and Previous entry^2 – to control for favorable conditions within the environment that may encourage niche entry (Delacroix & Carroll, 1983; Hannan et al., 1995).

Table 3.3 Definition of variables

Variable	Description
Component entry	Number of patents entering the focal component in the current month
Previous entry	Number of patents entering the focal component in the previous month divided by 1000
Organizational density	Number of organizations active in the focal component in the previous 12 months divided by 1000
System density	Cumulative number of patents in the focal system in the previous month excluding component density divided by 1000
Component density	Cumulative number of patents in the focal component in the previous month divided by 1000
Component diversity	Shannon's diversity index of the distribution of patents over sub-components in the focal component in the previous 12 months
Component status	Patent citations received by focal component in the previous 12 months divided by component density
Total crowding	Niche overlap between focal component and all other components in the previous 12 months divided by 1000
Local crowding	Niche overlap between focal components in the previous 12 months divided by 100
Global crowding	Niche overlap between focal and non-focal components in the previous 12 months divided by 100

Table 3.4 Summary statistics

Variable	Mean	SD	Min	Max	25th %	50th %	75th %
Component entry	5.017	14.354	0.000	217.000	0.000	1.000	4.000
Previous entry	0.005	0.014	0.000	0.217	0.000	0.001	0.004
Organizational density	0.034	0.077	0.000	0.666	0.001	0.008	0.029
Component density	0.669	1.628	0.001	15.139	0.022	0.085	0.571
System density	16.554	11.166	2.879	44.954	7.701	12.551	22.606
Component diversity	1.827	1.496	0.000	4.706	0.000	1.931	3.172
Component status	0.302	0.710	0.000	20.000	0.000	0.142	0.384
Total crowding	0.077	0.059	0.000	0.306	0.029	0.079	0.113
Local crowding	0.093	0.081	0.000	0.380	0.028	0.081	0.141
Global crowding	0.676	0.527	0.000	2.714	0.221	0.686	0.997

The high correlations among organizational density, component density, and previous entries imply high multicollinearity, which means we have to proceed with some caution.[11]

[11] Theoretically, multicollinearity is not a real issue, as our theory needs such a special model. Indeed, in by far the majority of empirical studies in the organizational ecology tradition, multicollinearity issues have to give way to what is required by theory. For example, to test the famous density dependence theory, density

Table 3.5 Correlation matrix

		1	2	3	4	5	6	7	8	9	10
1	Component entry	1.00									
2	Previous entry	0.93	1.00								
3	Organizational density	0.94	0.94	1.00							
4	Component density	0.88	0.88	0.95	1.00						
5	System density	0.11	0.12	0.15	0.10	1.00					
6	Component diversity	0.38	0.38	0.46	0.48	-0.08	1.00				
7	Component status	0.01	0.00	0.00	-0.02	0.17	-0.06	1.00			
8	Total crowding	-0.11	-0.11	-0.10	-0.12	0.25	0.10	0.08	1.00		
9	Local crowding	-0.08	-0.08	-0.07	-0.11	0.57	0.00	0.15	0.82	1.00	
10	Global crowding	-0.11	-0.11	-0.11	-0.12	0.20	0.11	0.07	1.00	0.77	1.00

3.4.2 Estimation

In ecological studies, the number of entrants is a natural and intuitive dependent variable to use. In organizational ecology, indeed, organizational founding studies abound. Similarly, the entry of inventions or patents in our technological components can be considered as an arrival process. Arrival processes count the number of arrivals to some state. The natural baseline model for arrival processes is the Poisson specification (Hannan & Freeman, 1989). A Poisson process is a pure birth process with a constant hazard, which means that duration dependence is assumed to be absent. In our case, that would imply patents entering our technological components at a fixed interval, independent of time and other covariates. Obviously, a pure Poisson model is far too simple for our purposes. A standard extension adds effects of covariates. This gives the Poisson regression model of the general form (Hannan et al., 1995)

(3.4) $$\Pr(y_i \mid x_i) = \frac{e^{-\lambda_i} \lambda_i^{y_i}}{y_i!}$$

(3.5) $$E(y_i \mid x_i) = \lambda_i = \exp(x_i \beta)$$

where λ_i is the deterministic function of the covariates.

However, using the Poisson distribution for modeling economic events involves quite strong and empirically questionable assumptions (Cameron & Trivedi, 1986, 1998). Empirical research on patent rates rarely finds that the mean of a time series of arrivals equals the variance, as a Poisson process implies. Instead, the variance tends to exceed the mean. This gives so-called overdispersion. The sources of overdispersion include, for instance, unobserved heterogeneity and time dependence (Carroll & Hannan, 2000).

There is a simple test to determine whether a sample suffers from overdispersion. That is, when comparing the sample mean and variance of the dependent count variable, if the sample variance is more than twice the sample mean, the data most likely suffer

and density squared have to be entered in the same model. The near-perfect multicollinearity in this type of models that emerges as an inevitable result does not undermine these models' value added.

from overdispersion (Cameron & Trivedi, 1998). The reason is that regressors reduce the conditional variance of the dependent variable, but usually with no more than 50 per cent in social science research (Cameron & Trivedi, 1998). Obviously, this also applies in the case of underdispersion. So, in the unlikely case that underdispersion does exist, this becomes even more pronounced after the inclusion of the regressors. As can be seen from Table 3.2, most of our components clearly suffer from overdispersion, as the dispersion parameter (i.e., variance/mean) is in many cases far greater than 2. We do need to acknowledge that three components might even suffer from underdispersion, namely components 435003, 435018 and 800006. For simplicity's sake, we choose to initially include these components in our analyses. However, we also estimate alternative models in which we exclude these components, compare the results, and report any inconsistencies that may arise.

One way to deal with overdispersion is to allow for inter-component heterogeneity by permitting component *i*'s arrival rate λ_i to vary randomly according to some probability law. When $f(\lambda_i)$ is assumed to be a gamma distribution, we have a negative binomial specification (Cameron & Trivedi, 1986). The Poisson model can thus be seen as a limiting case of the negative binomial specification, both models being equal when there is no overdispersion. Since the negative binomial specification allows for an additional source of variation, the estimated standard errors are larger, and the conclusions drawn are hence less precise (Hausman, Hall, & Griliches, 1984).

As mentioned previously, our data reflect a panel structure. Panel models accommodate for the existence of serial correlation (i.e., unobserved heterogeneity) between the repeated observations of the observed entities (Hausman et al., 1984), technological components in our case. A negative binomial panel model can be represented by the following equation (Benner & Tushman, 2002)

$$\lambda_{it} = \exp(x_{it}\beta + \gamma\varepsilon_i + \mu_i) \tag{3.6}$$

where x_{it} is a vector of characteristics of component i at time t, γ is a correction for overdispersion, and μ_i is a time invariant effect for each entity or component i, reflecting micro-level heterogeneity. This parameter can be treated as either fixed or random. The fixed effects model limits the variation used in the analysis to within-component estimates. In the random effects version, the entity or component-specific term is drawn from a specified distribution (Cameron & Trivedi, 1998). According to Hausman, Hall and Griliches (1984), the random-effects negative binomial specification, which is in effect a Beta distribution, allows the variance of the effects to differ in the within and between dimensions. Hence, adding random effects essentially produces a 'variance components' version of the negative binomial specification. The restriction for the random-effects specification is that the entity-specific term is not significantly correlated with the regressors. To determine whether this is indeed the case, Hausman's (1978) specification test can be used. Hausman's specification statistic is, basically, a test of the correlation between the regressors and unobserved heterogeneity or the error component in the model. The Hausman statistic is distributed as χ^2, and is computed as follows

$$H = (\beta_c - \beta_e)'(V_c - V_e)^{-1}(\beta_c - \beta_e) \tag{3.7}$$

where β_c is the coefficient vector from the consistent estimator, β_e is the coefficient vector from the efficient estimator, V_c is the covariance matrix of the consistent estimator, and V_e is the covariance matrix of the efficient estimator. The number of degrees of freedom for the statistic is the rank of the difference in the variance matrices.

It is important to control for unobserved heterogeneity in any analysis. However, in ecological studies, the potential problems that occur when not effectively dealing with unobserved heterogeneity are even more pervasive. As noted by Lomi (1995), models neglecting unobserved heterogeneity tend to overestimate the effect of density on founding rates. Regarding issues of unobserved heterogeneity or omitted variables bias, three options emerge (Podolny & Stuart, 1995): (a) do not control for quality differences at all; (b) treat quality differences as unobserved heterogeneity and device some method to control for these; and (c) rely on quality measures that are established in the relevant literature. In this chapter, we do both (b) and (c), as both niche density and previous entries are an operationalization of (b), and niche status of (c). Moreover, we use negative binomial dispersion models that account for unobserved heterogeneity (Carroll & Hannan, 2000). Finally, a panel structure controls for unobserved heterogeneity as well. Hence, unobserved heterogeneity should not be a problem in our analyses. To be completely confident, though, we will test for the presence of unobserved heterogeneity, as explained above.

As argued, the high correlation between our density measures (i.e., component density and organizational density) and the number of previous entries implies that we need to proceed with caution to ensure that our findings are not the result of multicollinearity. We therefore estimate alternative specifications of density dependence. Stability of our estimates over these alternative specifications increases our confidence that our findings are not the result of multicollinearity. In the organizational ecology literature, two models can be found to test the density dependence argument. The original model is known as the Generalized-Yule (GY) model, which is specified as follows

$$\lambda_{it} \propto C_{it}^{\alpha} \exp(\beta C_{it}^2) \tag{3.8}$$

where λ_{it} is the rate of entry in component i at time t, and C_{it} refers to the density of component i at time t. An alternative model is the Log-Quadratic (LQ) specification, which has the following form

$$\lambda_{it} \propto \exp(\alpha C_{it} + \beta C_{it}^2) \tag{3.9}$$

where, again, λ_{it} is the rate of entry in component i at time t, and C_{it} refers to the density of component i at time t.

To determine which model is better, we need to compare the functional specifications of the different models. Closer investigation shows that the major distinction between these specifications is how processes of legitimation are represented. The GY model allows for a decreasing positive effect only, while the LQ specification also allows for an increasing positive effect. According to density dependence theory, each additional entry contributes less to the legitimation of the population. Therefore, Hannan and Carroll (1992) have a preference for the GY over the LQ model as it connects better to the original theory. The authors further stipulate that when GY models do not converge or when LQ models result in a much better fit, LQ models can also be used. We thus estimate both the GY and LQ model, and select the model that provides for the better fit. We first investigate what the best representation is of organizational density, as this is an important control variable, by estimating both the GY and LQ model for organizational density. Next, we look for the appropriate representation of component density, again by estimating both specifications.

Our data involve left-censoring, as information is missing for the beginning of the history of the population – that is, biotechnology. Patent citation data are not available for the pre-1975 period. This does not imply a survivor bias, though, as we do have all cohorts: none are missing. However, this could still distort our results because we do not have the full lifespan of our technologies. We do not think this poses a severe threat to our analyses, as the majority of developments within biotechnology have taken place after the discovery of recombinant DNA in 1972. Moreover, due to changes in patent law (i.e., the so-called Bayh Doyle Act, which allows the patenting of research findings funded by means of federal grants), commercial activity within biotechnology only took off after 1980 (Sorensen & Stuart, 2000). Furthermore, we have data on a cross-section of different technologies within biotechnology, implying that several new and emerging technologies are represented. Nonetheless, we should still treat our findings with caution (Carroll & Hannan, 2000).[12]

3.5 Results

Tables 3.7 and 3.8 present estimates for the random-effects negative binomial dispersion model of patent counts. The models were estimated with the 'xtnbreg, re' command in Stata 8.0 SE. To ensure that our findings are not the result of multicollinearity, we build up our initial density dependence model incrementally using stepwise regression. To determine whether or not progressive model extensions imply a significant improvement in model fit, we follow standard practice and compare twice the difference in the Log-

[12] Processes of legitimation are especially important in the formative stages of population development. So, left-censoring might result in finding competitive effects only, due to an under-representation of processes of legitimation. Hence, this implies that we should be especially wary if we find no evidence for legitimation processes.

likelihood to a χ^2 distribution with degrees of freedom equal to the number of added variables. In doing so, stability of coefficient values over alternative models increases confidence in our findings. As argued, we estimate both the GY and the LQ specification for our density measures. The alternative models with which we start our analyses are displayed in Table 3.6.

The estimates of Models 1 through 6 are reported in Table 3.7. Note that the parameter estimates are not standardized, which means that the coefficient values should be exponentiated before interpretation. Moreover, the exponentiated coefficients represent multiplier effects on the rate of component entry.

Table 3.6 Alternative specifications for organizational, component, and system density dependence

NR	Type O	Type C	Type S	Specification
1	LQ	n.a.	n.a.	$\lambda_{it} \propto \exp(\alpha O_{it} + \beta O_{it}^2)$
2	GY	n.a.	n.a.	$\lambda_{it} \propto O_{it}^{\alpha} \exp(\beta O_{it}^2)$
3	GY	LQ	n.a.	$\lambda_{it} \propto O_{it}^{\alpha} \exp(\beta O_{it}^2 + \chi C_{it} + \delta C_{it}^2)$
4	GY	GY	n.a.	$\lambda_{it} \propto O_{it}^{\alpha} C_{it}^{\beta} \exp(\chi O_{it}^2 + \delta C_{it}^2)$
5	GY	GY	LQ	$\lambda_{it} \propto O_{it}^{\alpha} C_{it}^{\chi} \exp(\chi O_{it}^2 + \delta C_{it}^2 + \varepsilon S_{it} + \phi S_{it}^2)$
6	GY	GY	GY	$\lambda_{it} \propto O_{it}^{\alpha} C_{it}^{\beta} S_{it}^{\chi} \exp(\delta O_{it}^2 + \varepsilon C_{it}^2 + \phi S_{it}^2)$

Legend: NR = Model number; Type = Specification of density dependence; LQ = Log-quadratic; GY = Generalized Yule; O = Organizational density; C = Component density; S = System density.

Regarding the appropriate specification of organizational density, comparing the Log-likelihood values of Model 1 and Model 2 reveals that Model 2 provides for the better fit. The effect of organizational density on component entry has a similar pattern (i.e., a decreasing positive effect), the main difference being the magnitude of the effect (i.e., the GY specification has a much stronger effect than the LQ specification) and the location of the point of inflexion. As such, we are rather confident that our findings are not the result of multicollinearity between organizational density and previous entry.

Because Model 2 provides for the better fit, we continue with this model as the baseline for our subsequent analyses. That is, to determine the appropriate specification for component density, we include the GY specification of organizational density. Model 3 represents the GY specification of component density and Model 4 the LQ specification. Even though it appears as if the alternate specifications are highly dissimilar, the pattern of effects is largely similar, the major distinctions being twofold: (1) under the LQ specification, initially there is a slight negative effect of component density on component growth (i.e., up until a density of 11 inventions); and (2) the magnitude of the effect (i.e., again, the GY specification results in a stronger effect over the measure's normal range). Comparing the Log-likelihood values of Models 3 and 4 in Table 3.7 clearly indicates that the GY specification is superior in representing component density dependence as well. After all, the Log-likelihood of Model 4 is approximately 50 points higher (less negative) than Model 3's Log-likelihood value. So, now our baseline for subsequent analyses is a GY specification for both organizational and component density.

Next, we continue with investigating the appropriate specification of system density. Again, both the GY and the LQ specification are possible in this respect (see Table 3.6). As can be seen in Table 3.7, system density has a highly significant effect on component entry. However, in contrast to organizational and component density, the better fit is provided by the LQ specification (i.e., Model 5 in Table 3.7). Even though Model 5 reveals a significant negative coefficient for the quadratic term, the point of inflexion lies well above the maximum value of this measure, implying a decreasing positive effect (as expected).

The estimates of Models 7 through 10 are reported in Table 3.8. Model 7 adds component diversity, component status and total crowding to our baseline model (i.e., Model 5). Comparing the Log-likelihood value of Model 5 (-11,559) with that of Model 7 (-11,525) shows that Model 7 significantly improves model fit. After all, with a χ^2 of 24 (i.e., two times the difference in Log-likelihood) and three degrees of freedom, p is smaller than 0.01. Adding the interaction term of component status and total crowding in Model 8 does not significantly improve model fit (i.e., a χ^2 value of 0 with one degree of freedom, so $p = 0.16$).

Next, Model 9 makes a distinction between local and global crowding, significantly improving model fit. Compared to our baseline Model 5, Model 8 has a χ^2 of 74 with 4 degrees of freedom, so Model 8 has a significantly better fit than Model 5 (i.e., $p < 0.01$). Moreover, adding the interaction terms of, on the one hand, local crowding and niche status and, on the other hand, global crowding and niche status in Model 10 also significantly improves model fit, both compared to Model 5 (i.e., χ^2 value of 80 with 6 degree of freedom, so $p < 0.01$) and to model 9 (i.e., χ^2 value of 6 with 2 degree of freedom, so $p < 0.05$). As such, we use Model 10 to discuss the findings of our hypotheses. [13] We now continue with a discussion of results of our hypotheses.

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[13] Moreover, we have also estimated Model 10 using a fixed-effects specification, and conducted Hausman's specification test to investigate the extent to which the random-effects specification is indeed appropriate. As mentioned, this test compares the coefficient estimates of the consistent (i.e., fixed-effects model) and the efficient (i.e., random-effects model) estimator. When these estimates do not deviate significantly, the efficient estimation can be used as it provides (roughly) the same coefficient estimates as the consistent estimator. Unfortunately, this test fails to meet the asymptotic assumptions of the Hausman test. However, visual inspection of the coefficient values of both the fixed effects and the random effects specifications reveals no large discrepancies between coefficient values under the alternative specifications. Moreover, in previous analyses, Hausman's specification test has indicated that the random effects specification is indeed appropriate in our setting.

Table 3.7 Negative binomial random effects panel regression estimates of alternative density specifications

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Previous entry	8.191***	6.848***	8.112***	6.934***	8.090***	6.986***
	[1.764]	[1.040]	[1.192]	[1.011]	[1.046]	[1.033]
Previous entry^2	-22.175***	-16.343***	-21.457***	-17.418***	-23.0405***	-18.400***
	[8.173]	[4.665]	[5.265]	[4.607]	[4.811]	[4.706]
Organizational density	4.581***					
	[0.499]					
Ln(Organizational density*1000)		0.773***	0.775***	0.532***	0.523***	0.534***
		[0.021]	[0.022]	[0.032]	[0.032]	[0.032]
Organizational density^2	-6.180***	-0.799***	-0.460*	-0.869***	-0.151	-0.561**
	[0.559]	[0.156]	[0.271]	[0.240]	[0.299]	[0.268]
Component density			-0.0484**			
			[0.022]			
Ln(Component density*1000)				0.269***	0.292***	0.282***
				[0.026]	[0.029]	[0.029]
Component density^2			1.764*	0.234	0.621	1.891**
			[1.031]	[0.456]	[0.849]	[0.746]
Ln(System density*1000)						0.444***
						[0.155]
System density					0.084***	
					[0.020]	
System density^2					-0.001**	0.000***
					[0.000]	[0.000]
Constant	1.774***	-0.883***	-0.797***	-1.788***	-4.331***	-7.378***
	[0.074]	[0.103]	[0.112]	[0.138]	[0.461]	[1.661]
Observations	8,021	8,021	8,021	8,021	8,021	8,021
Number of components	27	27	27	27	27	27
d.f.	31	31	33	33	35	35
r	1.838	8.141	7.788	9.882	9.864	9.935
s	0.769	3.970	3.698	5.046	4.889	4.973
Log likelihood	-12,353	-11,630	-11,627	-11,578	-11,559	-11,563

Legend: * significant at 10%; ** significant at 5%; *** significant at 1%; standard errors in brackets.

Table 3.8 Negative binomial random effects panel regression estimates of full model

	Model 7	Model 8	Model 9	Model 10
Previous entry	7.729***	7.728***	7.322***	7.307***
	[1.048]	[1.048]	[1.065]	[1.061]
Previous entry^2	-22.254***	-22.251***	-20.760***	-20.798***
	[4.774]	[4.775]	[4.817]	[4.799]
LN(Organizational density*1000)	0.546***	0.546***	0.544***	0.543***
	[0.033]	[0.033]	[0.033]	[0.033]
Organizational density^2	-0.217	-0.218	-0.297	-0.315
	[0.302]	[0.302]	[0.304]	[0.304]
System density	0.082***	0.082***	0.083***	0.081***
	[0.020]	[0.020]	[0.020]	[0.020]
System density^2	-0.001**	-0.001**	-0.001**	-0.001**
	[0.000]	[0.000]	[0.000]	[0.000]
LN(Component density*1000)	0.319***	0.319***	0.322***	0.329***
	[0.031]	[0.031]	[0.031]	[0.031]
Component density^2	-0.034	-0.032	0.029	0.150
	[0.848]	[0.851]	[0.848]	[0.848]
Component diversity	-0.073*	-0.073*	-0.079*	-0.080*
	[0.041]	[0.041]	[0.041]	[0.041]
Component status (CS)	0.193***	0.193***	0.192***	0.194***
	[0.018]	[0.020]	[0.018]	[0.019]
Total crowding (TC)	-0.200	-0.194		
	[0.368]	[0.412]		
Interaction: CS * TC		-0.011		
		[0.344]		
Local crowding (LC)			-0.935**	-0.202
			[0.444]	[0.535]
Global crowding (GC)			0.07	-0.044
			[0.057]	[0.073]
Interaction: CS * LC				-1.550**
				[0.614]
Interaction: CS * GC				0.252**
				[0.102]
Constant	-4.190***	-4.190***	-4.218***	-4.230***
	[0.458]	[0.458]	[0.457]	[0.456]
Observations	8,021	8,021	8,021	8,021
Number of components	27	27	27	27
Degrees of freedom	38	39	39	41
r	9.358	9.359	9.205	9.308
s	4.353	4.353	4.283	4.352
Log likelihood	-11,525	-11,525	-11,522	-11,519

Legend: * significant at 10%; ** significant at 5%; *** significant at 1%; standard errors in brackets.

Hypothesis 3.1 argues that, due to processes of legitimation and competition, component density has an inverted U-shaped effect on component entry. This hypothesis is partially supported by our estimates because we only find a significant positive association between component density and component entry. So, only the legitimation part of this hypothesis is supported. Increasing density from its first quartile to its median value increases component entry with 55 per cent. Further increasing component density from its median value to its third quartile increases the rate of component entry with as much as 87 per cent.

According to Hypothesis 3.2, density at the system level is positively tied to component growth due to processes of legitimation at the system level. This hypothesis is fully supported by our findings. We find a consistent and highly significant positive effect for system density. Even though a significant negative coefficient is found for the squared term, this only results in a decreasing positive effect as the point of inflexion lies well outside this measure's normal range, and even above its maximum value. That is, in Model 10, the point of inflexion is -0.0806/(2*-0.0006) = 67, while the maximum value for system density is 45 (i.e., 45,000 inventions). Regarding the effect of system density, subtracting a standard deviation from its mean value reduces component entry with 112 per cent, while adding a standard deviation to its mean value increases the rate of entry with 81 per cent.

Hypothesis 3.3 posits that component diversity is positively associated with the rate of component entry. This hypothesis is rejected by our estimates. Instead of a positive effect, we find a significant negative effect in all models that include diversity (i.e., Models 7 to 10). In Model 10, increasing the value of component diversity with one standard deviation decreases the rate of component entry with 11 per cent.

Our analyses do substantiate Hypothesis 3.4, which claims that the main effect of component status on component entry is positive, by providing an anchor for investment in an uncertain environment. Although small, we do find a significant effect. Increasing the value of component status from its 1^{st} quartile to its median value increases the rate of component entry with 3 per cent, and increasing component status from its median value to its 3^{rd} quartile increases growth with 5 per cent.

We also find full support for Hypothesis 3.5. According to this hypothesis, local crowding has a negative effect on component entry due to competitive processes. As can be seen in Models 7 and 8 in Table 3.10, crowding does not have a significant effect on component growth until separated into its local and global representation. The coefficient for local crowding is highly significant and negative. In Model 9, increasing local crowding with one standard deviation decreases the rate of component entry with 7 per cent.

In contrast to Hypothesis 3.5, we do not find full support for Hypothesis 3.6. This hypothesis states that global crowding is positively associated with component entry as a result of positive spillovers or network externalities. Even though we do find a positive coefficient for this variable, it is far from significant. However, in interaction with component status, we do find some support for the existence of positive spillovers.

Finally, Hypothesis 3.7 argues that the interaction of local crowding and component status is negative due to the formation of clique-like structures in locally (and not globally) crowded niches. This hypothesis is fully supported by our estimates, as we find a highly significant negative coefficient for the interaction term between component status and local crowding. Moreover, the interaction between component status and global crowding is positive and highly significant. Figures 3.4 and 3.5 visualize the effects of the interactions between these variables. As can clearly be seen, on the one hand, component status has a negative effect at high levels of local crowding. On the other hand, at high levels of global crowding, component status not only retains its positive effect on component entry, but this positive effect becomes even more pronounced.

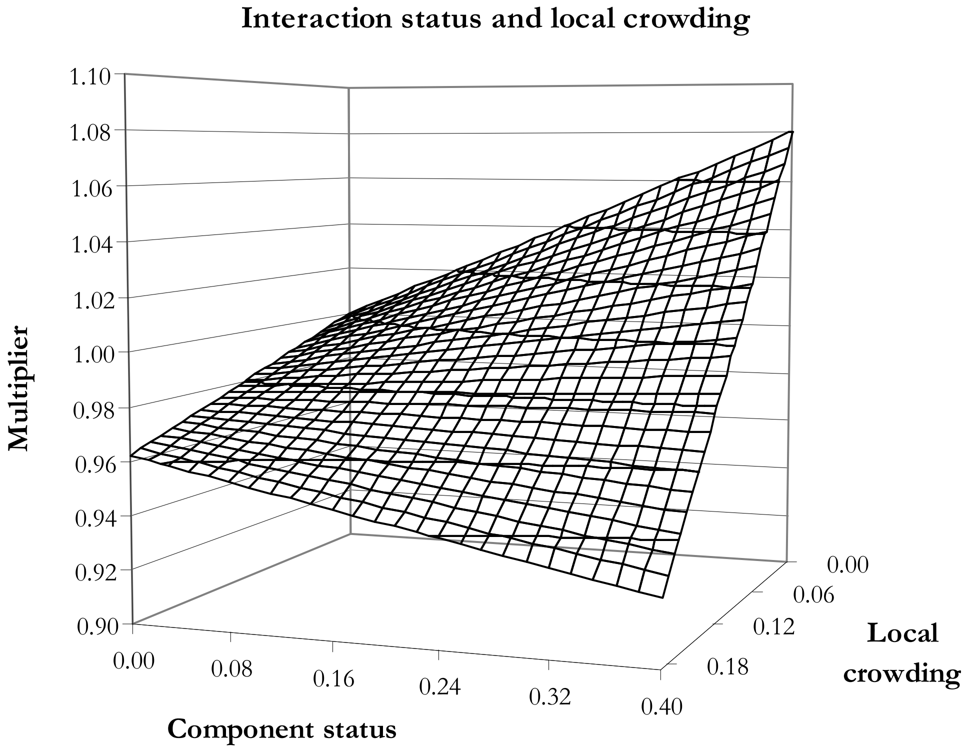

Figure 3.4 Interaction component status and local crowding

Regarding the results for our control variables, we want to note the following. To control for year-specific effects, we have included year dummies in our analysis (not reported here, for the sake of brevity: available upon request). No trend can be depicted from the period before 1992. Although many individual years have a significant effect on niche growth, a clear evolution in either way cannot be observed. However, after 1992, a clear downward trend emerges, where each consecutive year further decreases component growth, with the exception of 1996. An in-depth investigation of this downward trend in the post-1992 period would definitely be interesting, but is outside the scope of this chapter. Next, with respect to the effect of previous entry, the coefficient for the linear term is positive and highly significant while the coefficient for the squared term is negative and highly significant, indicating a curvilinear effect of previous entry on subsequent entry. The point of inflexion (i.e., 0.18 or 180 inventions) lies well beyond this measure's normal range, implying that previous entry increases subsequent entry at a decreasing rate. Finally, as already mentioned, organizational density has a highly significant effect on component growth. Increasing organizational density from its 1st quartile to its median value increases the rate of component entry with 156 per cent, while increasing the number of organizations from its median value to its 3rd quartile further increases component entry with another 97 per cent.

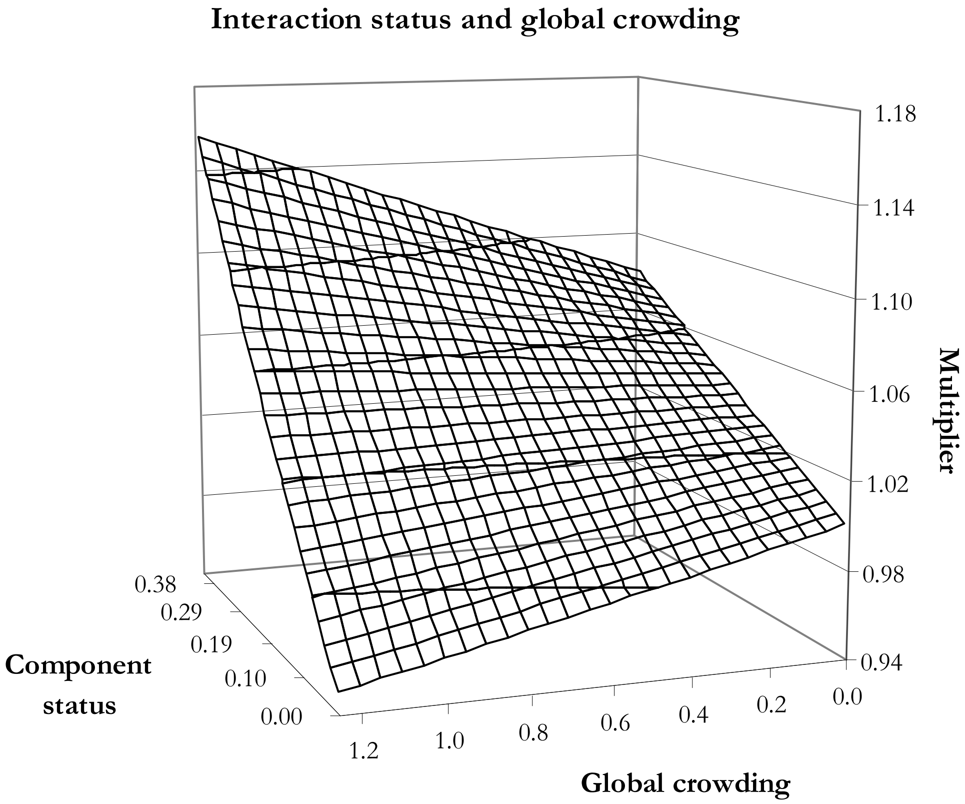

Figure 3.5 Interaction component status and global crowding

3.6 Discussion and conclusion

Even though technology fuels economic growth, the question of how technological changes come about endogenously has been left largely unanswered. One of the main reasons for this blind spot is that most studies view technology as a single component, without considering its multi-level nature. That is, these studies ignore the embeddedness of this component within a larger technological system, and thereby disregard the interdependence between components (Rosenkopf & Nerkar, 1999). Hence, a systemic or structural perspective is relatively underdeveloped. This study has addressed this gap, both theoretically and empirically, by developing and testing what we will coin the 'ecology of technology'. The pattern of significant findings provides clear evidence for an ecologic dynamic of technological components within a technological system. Many ecological variables significantly impact upon a focal component's growth (see Table 3.9). In all, we find full support for four hypotheses, and partial support for one. So, we believe that the 'ecology of technology' proposed here is certainly promising, by applying ecological logic at the level of a technological system. Of course, our study is only a first step. Unexpected findings and design limitations offer steppingstones for future work. Here, we would like to reflect on four of these.

Table 3.9 Overview of our hypotheses and findings

Hypothesis	Expected	Found	Significance	Result
3.1 Components density	∩	↑	***	Partially supported
3.2 System density	↑	↑	***	Supported
3.3 Component diversity	↑	↓	*	Rejected
3.4 Component status (CS)	↑	↑	***	Supported
3.5 Local crowding (LC)	↓	↓	***	Supported
3.6 Global crowding	↑	↑		Not supported
3.7 Interaction CS & LC	↓	↓	***	Supported

Legend: * Significant at 10%; ** significant at 5%; *** significant at 1%.

First, in developing a systemic view towards technological growth, we have assumed that our technological system is stable, with technological components behaving in reliable and predictable ways. In doing so, we have been able to demonstrate that biotechnology – or any other technology, for that matter – can effectively be studied as a technological system, composed of a set of interdependent and interacting technological components. However, by no means does this imply that we perceive technology as a stable system, with components behaving in reliable and predictable ways. Even though we acknowledge that some technologies could, at a certain point in time, be characterized by such a system-state, at this moment, biotechnology is most definitely not one of them. On the contrary, biotechnology can be characterized as a highly dynamic technology, with many components that are just being developed (e.g., consider the mean of the entry of inventions into component 800006 with the mean of component 435004 in Table 3.2). Obviously, this implies that the patterns of interactions between biotechnology's components have not yet stabilized. So, we have merely developed a steppingstone for the analysis of technology as a set of interdependent components. That is to say, our model needs to be extended to investigate the dynamics between these components over time. As such, this could enable a distinction between the system's core and peripheral components (Tushman & Murmann, 1998). In turn, this would allow for studying the evolution of a technological system, driven by the evolution of its core components (Rosenkopf & Tushman, 1994).

This naturally brings us to our second point – the evolution of technological components. In contrast to our expectations, we found a significant negative effect of component diversity on component growth. This seems to point to the presence of competition between sub-components, which hampers the legitimation of the component within the larger environment. As such, it connects to the literature on dominant designs (Utterback & Abbernathy, 1975), originally conceived at the product level, but recently found to be more relevant at a component level (Tushman & Murmann, 1998). According to this literature, on the one hand, before a dominant design exists, actors recombine sub-components and interact socially in an effort to find or become part of the dominant configuration that will serve as the basis for the future development of the technological component. On the other hand, after a dominant design emerges, actors no longer invest in alternative configurations and focus their attention on working out the sub-component configuration represented in a dominant design. Our results thus point to the second stage of development, after a dominant design has been established. After all, in this stage, additional diversity does not contribute to the legitimation of the component and merely thwarts resources from the (explicitly or implicitly) agreed upon sub-component configuration represented by a dominant design. It thus seems that diversity, like density, plays a twin role in the evolution of a technology. As such, we expect that studying the role of diversity more directly in the evolution of technologies could lead to a better understanding of processes of endogenous technological change. In developing such a theory of diversity dependence in technological populations, both centripetal and centrifugal forces would have to be taken on board (Hawley, 1986). That is, we need a theory explaining when diversity stimulates or dampens technological growth (cf. Boone et al., 2004).

Third, an important limitation of our study is that we have abstracted from the role of the innovating organization. After all, our results clearly indicate that organizations play a major role in the growth process of a technological component. This signifies the importance of developing a co-evolutionary model, where both the evolution of technologies and the evolution of organizations are considered in unison. After all, it is well-recognized that technologies and organizations co-evolve (Anderson & Tushman, 1990; Rosenkopf & Nerkar, 1999). Here, we would like to briefly reflect on two obvious contributions that could be made when developing such a model. First of all, it could lead to a theory that explicates the role of different organizational forms in a model of endogenous technological change. Technological change plays a key role in the creation of new organizations, and especially in the creation of new forms of organizations (i.e., form emergence). Each wave of technological change produces new sets of opportunities. While sometimes these opportunities are exploited by members of existing organizational forms, quite often only new organizational forms can effectively meet the requirements that arise from the application of new technology (Hannan & Freeman, 1989).

Moreover, at the level of an individual organization, we can relate the dynamics of technological components to the characteristics of an organization's technological search behavior. Organizations search as members of a population (Podolny & Stuart, 1995), and by focusing on technology we basically investigate the search pattern of a population of organizations (i.e., a technological community or industry). By relating an individual organization's technological search to the pattern of search at the organizational population level, it is possible to determine whether the organization's search behavior conforms to or conflicts with this aggregate search pattern. This links to work done by Fleming (2001), who finds an increase in the level of uncertainty and potential payoff of individual inventions when these inventions use more novel combinations. Moreover, this also connects to March's (1991) notions of exploration and exploitation, and enables a simultaneous distinction between processes of exploration and exploitation at the organizational level and the level of an organizational population (i.e., industry or community).

Fourth and finally, another limitation is that our empirical setting is the domain of biotechnology. Studying this technological domain has the advantage that patents form a reliable indicator of processes of technological growth (Orsenigo et al., 2001; Powell et al., 1996), hereby enhancing the internal validity of our study. However, a study into a single domain generally puts limits on the extent to which our findings can be generalized. Biotechnology reflects a highly science-based innovation pattern, with an important role for universities and research institutes. This clearly differs from technologies that are developed through inter-firm interaction, such as (lead) users and (specialized) suppliers (Pavitt, 1984). So, different technologies are embedded in different patterns of interaction, which has consequences for the process of recombination. Studying such differential effects should be high on the agenda of future research in the realm of the 'ecology of technology'.

Chapter 4

The Evolution of Technology

4.1 Introduction

In the previous chapter, we have argued that a structural or systemic perspective on technology is missing. Due to the hierarchical nature of technology, therefore, most studies on the evolution of technology are rather idiosyncratic and atheoretical (Rosenkopf & Nerkar, 1999). So, in an effort to contribute to the development of a structural or systemic perspective on technology, we have developed what we coin the 'ecology of technology', by applying logic from organizational ecology to technological growth. In doing so, we have been able to elucidate some of the multi-level processes that drive technological growth. However, even though such a systemic perspective certainly contributes much to our understanding of the dynamics of technological change, the model itself was of a highly static nature. That is, we have assumed that technological growth is characterized by stable processes. Obviously, this poses severe limitations to the development of a formal model on the evolution of technology, which has already resulted in some anomalous empirical findings in the previous chapter. More specifically, contrary to our expectations, we have found a negative effect of component diversity on component growth. We have suggested that this might be related to different stages of technological development. In the current chapter, we investigate whether this is indeed the case.

A vast amount of literature identifies two stages of technological development (or evolution), and generally distinguish between a stage of social construction and a stage of technological determinism (Rosenkopf & Tushman, 1994). Some of the better known examples are the work on dominant designs (Utterback & Abbernathy, 1975), technological guideposts (Sahal, 1985), the structuration of technology (Orlikowski, 1992), technological paradigms (Dosi, 1982), technological focusing devices (Rosenberg, 1976), punctuated equilibria theory (Rosenkopf & Tushman, 1994), product architectures (Henderson & Clark, 1990), and design hierarchies (Clark, 1985). Even though these literatures are extremely insightful, unfortunately, they mostly rely on rather subjective judgments and qualitative assessments to distinguish between these different stages of technological development. This stands in the way of the development of a formal theory of the evolution of technology. Moreover, because technology structures the relationship within and between organizations and industries, it also stands in the way of a thorough investigation of the evolution of organizations and industries. After all, technology drives the evolution of organizations and industries, and a detailed understanding hereof also requires a thorough understanding of the evolution of technology.

As it is our objective to contribute to the development of a formal theory of the evolution of technology, in the current chapter, we explore the extent to which we can apply formal quantitative models to distinguish between these different stages of development for an emerging (i.e., non-mature) technology. Several quantitative models are found in life cycle theory, which relies on the analysis of technological growth patterns to distinguish between different stages of development. However, as we will demonstrate in this chapter, unfortunately, these models are not really adequate when dealing with an emerging technology (e.g., biotechnology). The reason is that most of these models apply an *ex post* perspective to the evolution of technology. We therefore choose to develop an alternative, multi-level model, which is more tailored at the study of emerging technologies. After all, the evolution of technology is an inherently multi-level process (Tushman & Nelson, 1990). Using this model, we are able to distinguish between the two stages of technological development, and to demonstrate that these stages are characterized by distinct evolutionary processes. Moreover, by further taking the lineage of technology into account, we dig deeper into the embeddedness of our component niches in the technological landscape. More specifically, we add antecedent and descendant diversity as dimensions to the technological niche, and demonstrate that these significantly impact technological growth, and therefore technological evolution.

The contribution of this paper is fourfold. First, we demonstrate that the components of an emerging technological system can be characterized by two stages of technological development, with distinct evolutionary processes that can be related to the twin processes of knowledge creation (i.e., the creation of a stable technological design configuration) and diffusion (i.e., the diffusion of a stable technological design configuration). In doing so, besides further illuminating the extensively studied process of knowledge diffusion, this also allows for the systematic analysis of knowledge creation processes, which have received much less scholarly attention. In this way, we increase our understanding of the evolution of technology, and how the processes of creation and diffusion relate to one another. Second, we develop a (hierarchically-nested) multi-level model of the evolution of technology, which permits to investigate of the emergence of technological stability and, hence, path dependence.

That is, using this model, we can analyze how stable technological design configurations travel upwards that result in predictable patterns of growth and development at higher levels of analysis. As such, we further contribute to the development of a formal model of the evolution of technology, based upon microstate assumptions or microeconomic behavior. Third, by further taking into account the lineage of technology, we are able to extent the notion of the technological niche, and add the diversity of the niche's antecedent and descendant technology as substantive dimensions. Fourth and finally, in doing so, we further illustrate the value of combining evolutionary and ecological models in the study of technology, and provide a platform for the future study of the co-evolution of technologies and organizations.

Regarding the organization of this chapter, Section 4.2 discusses the literatures on the evolution of technology, and develops associated hypotheses. Next, in Section 4.3, we discuss technological diversity and, again, formulate related hypotheses. Subsequently, Section 4.4 outlines our empirical sample and estimation methods. We discuss our results in Section 4.5. Finally, Section 4.6 discusses the limitations of our study, places our findings in the broader academic debate, and develops several thoughts on interesting avenues for further research.

4.2 Evolution of technology

Even though some pioneer economists already recognized the importance of technological progress (Marx, 1906), they generally captured technological change as a mere shift along the production function. As a result, the process of technological change has largely remained unexplored. This changed when Schumpeter (1934) presented an evolutionary theory of the workings of the capitalist system, driven by forces of technological change. Schumpeter (1939) conceived technological change as a process of recombination, where (existing) components are brought together in new ways. Since then, the process of technological change has no longer been treated as a 'black box' (Rosenberg, 1982), and has been – and still is, for that matter – receiving much attention. Especially the field of evolutionary economics, with at its heart a process of endogenous technological change, has contributed much to our understanding of the process of technological change. According to evolutionary economics, due to an agent's limits in information-processing and problem-solving capacity, or bounded rationality (Simon, 1957), there is a need to search and recombine locally from a limited set of components (Fleming, 2001). After all, if the number of components that an agent considers grows linearly, the number of potential (re-)combinations that can be made with these components and its associated cognitive load grow exponentially (Hannan et al., 2007). Therefore, agents rely on heuristics to reduce the cognitive load, rather than applying strict and rigid rules of optimization (Simon, 1957).

At the organizational level, these heuristics translate into organizational routines that ensure regular and predictable patterns of behavior (Nelson & Winter, 1982) that result in organizational inertia (Hannan & Freeman, 1984) and path dependence. In the context of technological development, these heuristics are reflected in stable and predictable patterns of technological growth, which are well-documented in the received literature. According to Utterback and Abernathy (1975), technological development evolves from an uncoordinated process, characterized by fluid and unsettled relationships, into an efficient and tightly integrated system with highly specialized and interdependent actors. Rosenberg (1976) argues that technology acts as a focusing device, where typical problems, opportunities and targets direct technological search (i.e., growth and development) in particular directions. Following Sahal (1981), technological guideposts and basic designs lay out definite paths of developments characterized by long periods of incremental improvements. In building upon Kuhn's (1996) notion of scientific paradigms, Dosi (1982) posits that the characteristic habits and routines in searching and problem solving on the ground of a technological paradigm result in path-dependence. And, according to Clark (1985), as development proceeds, technological diversity gives way to standardization, where performance criteria and processes are more clearly specified. Moreover, Anderson and Tushman (1990) distinguish between long eras of cumulative, incremental changes, on the one hand, and concise periods of ferment (i.e., brief periods of major discontinuities), on the other hand.

This is just a small selection of research regarding stable patterns of technological development and growth. However, even though these literatures surely add considerable insight as to our understanding of the evolution of technology, they do not explicitly consider the fact that technology is embedded within a larger technological system, hereby largely ignoring the multi-level or systemic nature of technology. As the phenomenon of technology is inherently multi-level in character (Tushman & Nelson, 1990), developing a systemic, multi-level model of the evolution of technology can add insights above and beyond a singular perspective. After all, a multi-level model allows for an analysis of how stable and predictable patterns emerge at lower levels of analysis, and how these travel upwards in the hierarchy of technology (Barley, 1990).

In the previous chapter, we have already developed a systemic and multi-level model of technological growth. There, we demonstrated that biotechnology can be effectively studied as a technological system, with interdependent technological components. To do so, we relied on the limiting assumption that the system's components are characterized by a stable pattern of behavior (i.e., by assuming fixed coefficients values over time). Because system behavior is an aggregation of its constituent components' behaviors, this implies that we also assumed that the system itself is characterized by stable and predictable patterns of behavior. In other words, we took biotechnology to be a mature technology. This is a debatable assumption for two obvious reasons. First of all, it cannot be merely assumed that a technology spontaneously comes into existence as a mature technological system, associated with stable and predictable patterns of behavior. Second, even though biotechnology displays systemic properties, by no means can it be considered as a mature and, therefore, highly integrated technological system (cf. Paragraph 2.5). Therefore, it is the aim of this chapter to develop a more dynamic version of our systemic model.

As mentioned, biotechnology is an emerging technology, not yet characterized by stable and predictable patterns of development. Or, put differently, a dominant configuration of biotechnology's component technologies is missing. After all, a dominant configuration of biotechnology's components is only possible after (1) biotechnology's principal components have been identified, and (2) these key components have become characterized by stable and predictable patterns of development. That is, through a process of recombination, the 'optimal' component configuration has been found that can be further improved upon. This implies that stable linkages (i.e., patterns of interaction) have developed between the system's principal components. So, in accordance with Hawley (1950), instead of looking at the evolution of the system as a whole, we can focus our attention on the evolution of biotechnology's principal components. In doing so, we will also get more insight into the evolution of an emerging technological system as a whole. Hence, again, we conceive of technology as a system composed of a set of interdependent components. However, instead of assuming that the system is stable, we allow the system's components to evolve over time. More specifically, we argue that the system's components can be characterized by two stages of technological development.

4.3 Stages of technological development

In Figure 4.1, we define the key elements of our conception of a technological system.

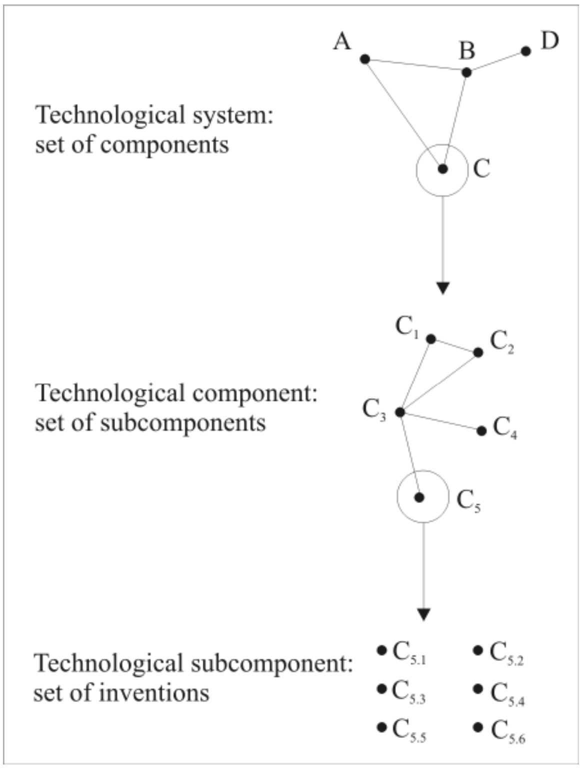

Figure 4.1 A technological system composed of components, subcomponents, and inventions

Moreover, as mentioned, technological evolution can be characterized by two stages of development. Initially, in the divergence or seed stage, technology is socially construction by the technology's stakeholders in the environment and developments are characterized by highly fluid patterns. This is in stark contrast with the subsequent convergence or growth stage, where stakeholders converge towards an agreed upon technological design configuration, and developments are much more of a path dependent (i.e., technologically deterministic) nature. These stages are visualized in Figure 4.2.

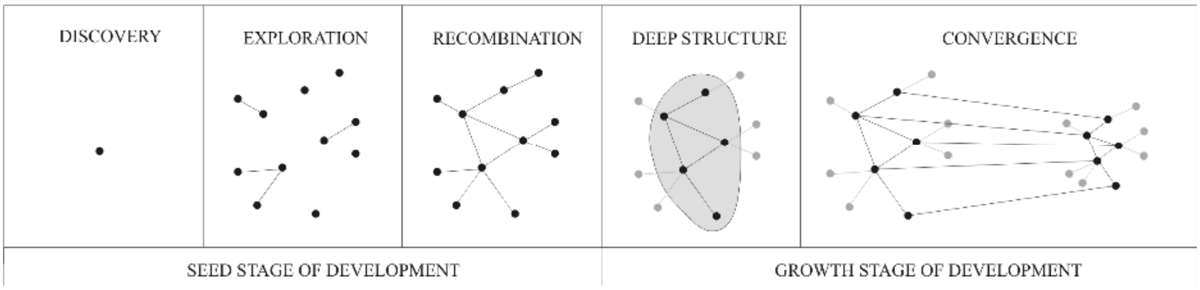

Figure 4.2 Characteristics of the different stages of technological development

In the beginning, just after a technological component is initially conceived (i.e., the discovery phase in Figure 4.2), developments within this newly discovered technological domain are characterized by chaotic patterns of search in highly uncertain environments. At the outset, these search patterns are directed at discovering the principal subcomponents of the newly discovered technological component (i.e., the exploration phase in Figure 4.2). After the principal subcomponents have been identified, they are combined with one another to find the dominant subcomponent configuration of the principal technological component (i.e., the recombination phase in Figure 4.2). Before a dominant subcomponent configuration has been established (i.e., in the seed stage of development in Figure 4.2), each set of actors (i.e., organization, group of organizations, and even entire communities) develops its own subcomponent configuration, accompanied with a unique set of performance criteria and specific motives as to why this subcomponent configuration is the better alternative.

Because the principles (i.e., the subcomponent configuration) on which technological growth should be based are yet unknown, competition among legitimate methods, heuristics and designs ensues (Kuhn, 1996). Hence, this stage can be characterized by a high level of technological uncertainty. Moreover, because actors basically have to consider all possible alternatives, the cognitive burden is enormous, and resource distributions and research efforts are of a highly fragmented nature. For progress to be made, a deep structure (see Figure 4.2) or dominant subcomponent configuration is required, with stable and clear performance criteria that make it possible to compare competing practices (Nelson, 2008). In this stage, because objective criteria do not yet exist, actors must rely on their social and networking skills to generate enough support among the appropriate set of stakeholders (e.g., investors, employees, government agencies, consumers and suppliers). Only when there is (implicit or explicit) agreement on the dominant subcomponent configuration of the technological component (i.e., in the growth stage of development) does cumulative growth become possible. Hence, the transition from this seed stage of chaotic development to a growth stage of ordered development is not so much a technical, but rather a sociological one (Anderson & Tushman, 1990).

To reiterate, to enable cumulative technological development, actors must agree upon a dominant subcomponent configuration to provide the needed stability and reduce the level of uncertainty. This stage – to which we will subsequently refer as the growth stage of technological development – is characterized by convergence towards the collectively agreed-upon or socially-constructed dominant subcomponent configuration (i.e., the convergence phase in Figure 4.2). Hence, the stable subcomponent configuration provides a heuristic that directs the agent's (i.e., stakeholders) search processes and enables specialization. This stage can therefore be characterized as technologically deterministic, as agents structure themselves according to the agreed-upon dominant subcomponent configuration. In other words, actors stop investing in alternative configurations and are able to focus their attention on working out the dominant subcomponent configuration (Henderson & Clark, 1990).

Over time, these patterns of behaviors stabilize as formal structures and routines become institutionalized (Cyert & March, 1963). Even though each incremental step might appear quite small, the cumulative economic consequences of incremental change are enormous (Hollander, 1965). After all, this dominant subcomponent configuration facilitates compatibility and integration in the technological system and wider technological environment (Baum, Korn, & Kotha, 1995; Katz & Shapiro, 1986). Hence, the technological component becomes skilled at what it does (Gersick, 1991), and becomes tightly coupled with and integrated in the technological system and overall technological landscape in which it is embedded through the development of formal governance structures.

We are now ready to adapt our arguments from the previous chapter, while considering the existence of two different stages of technological development. First, in this section, we focus on the elements of our model that are not related to technological diversity. In the next section, we then add a new twist to the treatment of technological diversity.

4.3.1 System density

First, regarding system density, when a technological component is initially discovered, it is unclear how this component relates to the other (if any) components in the technological system, and linkages among the focal and other components have yet to be developed. This means that subcomponents are missing that link the focal components to the other components in the system.[14] Hence, the component and the system to which it belongs evolve rather independently from one another. Essentially, actors (i.e., organizations) need to (re-)combine the focal component with the system's alternative component, to find the component's dominant subcomponent design configuration (i.e., its role in the technological system). Hence, initially (i.e., in the seed stage of development), the component is not yet legitimated at the system level, because the role of the component within the system is still unclear. As such, we do not expect to find a significant relationship between system density and component growth in this stage.

However, this changes when stable and reliable patterns of interaction develop between the focal and the alternative components of the system. Now, the role or the added value of the component in the technological system becomes apparent, and the component is legitimized at the system level. So, as the component forms an integral and essential part of the technological system as a whole, legitimation processes at the system level start to contribute to component growth, and the component is in the growth stage of development. We thus formulate our first hypothesis as

Hypothesis 4.1: *System density is positively associated with component growth in the growth stage of technological development.*

4.3.2 Component density

In the previous chapter, we have argued that component density is tied to processes of legitimation and competition. Because we only found a positive main effect of component density on component growth, we argued that only the legitimation part of our hypothesis is supported. However, according to density dependence theory, legitimation increases at a decreasing rate (Carroll & Hannan, 2000). Because we did not find a decreasing positive effect in the previous chapter, component density might not be the best proxy to represent the legitimation process of technology. But, if this is indeed the case, what then caused the positive effect of component density on component growth? An obvious answer is network externalities or positive spillovers. After all, the connection between density and network externalities is well-established (Delacroix & Rao, 1994; Dosi, 1982; Jaffe, 1986; Wade, 1995). If density is indeed tied to positive externalities, it should have a significant positive effect in both stages of technological development, and this positive effect should not be significantly weaker in the growth stage of development. Our next hypothesis thus becomes

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[14] Initially, these linkage technologies (i.e., subcomponents) are developed in the component itself. In a later stage, this can eventually flesh out into full-blown components.

Hypothesis 4.2: *Component density is positively associated with component entry, and the positive effect is not significantly weaker in the growth stage of development.*

4.3.3 Organizational density

In the previous chapter, we abstracted from the organization, and merely included organizational density as a control in our analyses. The strong effect of organizational density on component growth signifies that organizational density plays a highly important role in the development of technology, though. In conjunction with our finding that component density might not be a good proxy for the legitimation process of technology, we suggest that the legitimation of technology is mainly tied to the number of organizations adopting the technology (Duysters, 1995). This is the result of a process called mimetic isomorphism, where, under conditions of high uncertainty, actors imitate each others' behavior (Dimaggio & Powell, 1983). This process is mainly important in the seed stage of the component's development, when the component's role in the system is unknown, objective performance criteria are absent, and development is characterized by extreme levels of uncertainty. As a result, actors have to resort to alternative means to determine whether the component is worthy of their resources and attention, and imitate one another's behavior.

Hence, especially in the seed stage of development, organizational density has a legitimating effect on technology and, therefore, a positive effect on component growth. Obviously, in the growth stage of development, legitimation of technology remains important, and technological developments are still characterized by high levels of uncertainty. However, as the role of the component is outlined in the (implicit or explicit) dominant subcomponent design configuration, uncertainty is significantly lowered, and legitimation processes start to operate more and more at the system level. Therefore, we expect legitimation effects of organizational density to be less strong in the growth stage of development. In conclusion, we expect a stronger positive effect of organizational density on component growth in the seed stage than in the growth stage of a technological component. So, our next hypothesis is

Hypothesis 4.3: *Organizational density is positively associated with component growth, and more strongly so in the seed stage of development.*

4.3.4 Component status

As mentioned previously, in environments characterized by high levels of uncertainty (i.e., in the seed stage of development), resource controllers cannot rely on objective quality measures of technology (Podolny & Stuart, 1995). As a consequence, resource controllers need other means to decide where to invest their scarce resources (such as capital, product demand, and endorsements). Hence, resource controllers or stakeholders 'scan' the environment for signals to determine whether a certain technological component deserves their attention and resources. In the previous section, we already stated that the number of organizations that adopt the technological component contributes significantly to that component's legitimacy. An alternative and well-known proxy for the amount of legitimacy of an entity is its status or reputation in the wider environment (i.e., among resource controllers and stakeholders). In the context of technological development, status refers to the importance of the component's contributions to previous technological developments, and higher status components attract a greater amount of resources, by providing an anchor for investments in murky waters. Because the seed stage of technological development is characterized by much higher levels of uncertainty than the growth stage of development, component status has a stronger effect on component growth in the seed stage of development. This gives

Hypothesis 4.4: *Component status is positively associated with component growth, and more strongly so in the seed stage of development.*

4.3.5 Component crowding

In the previous chapter, we already stipulated that component crowding is tied to competition, as it implies an overlap in resource requirements (Hannan & Freeman, 1977), and therefore has a negative effect on component growth. However, due to knowledge and reputation spillovers (Fleming & Sorenson, 2004; Jaffe, 1986; Levin, 1988), economies of standardization through sharing of infrastructure (Baum & Haveman, 1997; Wade, 1995) and vicarious learning (Delacroix & Rao, 1994), component crowding also contributes positively to component growth. On the basis of the localized competition hypothesis (Barnett, 1997), we made a distinction between local and global crowding to disentangle the twin effects of crowding. Here, we take a slightly different approach. That is, we explore the extent to which we can disentangle the twin effects by distinguishing between the different stages of technological evolution.

In the seed stage, technological developments are of a highly uncertain nature, as the configuration of the component and its role within the system are still unclear. In this stage, using highly crowded, well-developed and, therefore, legitimated components reduces some of the uncertainty surrounding the developments, which results in positive knowledge and reputation spillovers that contribute positively to the component's development. Hence, in the seed stage of development, component crowding is tied to positive externalities, as the component benefits from the legitimation and institutionalization of the knowledge base (i.e., resources) on which it builds.

In the growth stage, in contrast, uncertainty is significantly lowered as the dominant subcomponent configuration provides stability by guiding technological developments and specifying the added value of the component in the technological system. Now, using highly crowded and well-developed components implies less room for technological developments, and a depletion of technological options surrounding the technological component. This implies that there is less room for improvements or maneuvering at all, as all key developments are already history. Consequently, component crowding has a negative effect on component growth in the growth stage of development. Hence, we have

Hypothesis 4.5: *Component crowding is positively (negatively) associated with component growth in the seed (growth) stage of development.*

4.4 Technological diversity

In the previous chapter, we have argued that technological diversity plays a key role in the evolution of technology. However, instead of the expected positive association between component diversity and component entry, we instead found a significant negative effect of component diversity on component growth. We have already suggested that this finding seems to point to the existence of different stages of technological development, too, and to the key differential role of diversity in these different stages. Therefore, in the current chapter, besides merely considering the role of component diversity, we dig deeper into the concept of technological diversity in the different stages of technological development. More specifically, in the previous chapter, we illustrated that, when considering the lineage of technology, it is possible to distinguish between a focal invention, the antecedent inventions on which the focal invention builds, and the descendant inventions that build upon the focal invention (cf. Figure 1.3). Obviously, this logic not only applies to individual inventions, but can also be applied at higher levels of aggregation. That is to say, at the component level, the antecedent technology refers to the set of inventions on which the component builds, while the descendant technology refers to the set of inventions that build upon the component's technology. Therefore, besides considering the role of component diversity in component growth, we also consider the extent to which the diversity of the antecedent and descendant technology impact the focal component's growth.

4.4.1 Component diversity

Component diversity represents the degree to which technological development within the component takes place within different subcomponents. As we already suggested in the previous chapter, this has different implications in the different stages of technological development. On the one hand, in the seed stage of development, more subcomponents imply more alternative subcomponent configurations, which is associated with more flexibility that prevents lock-in or path dependence (Stirling, 2007). In this respect, component diversity represents the broadness or niche width of the technological component. The broader the appeal of the component to resource controllers, the more the component is able to mobilize resources from these actors in different regions of the technological environment, which stimulates component growth. Moreover, increasing the number of subcomponents also increases the potential for their recombination. The greater this recombination potential, the greater the technological opportunities within this component and therefore the greater the potential value of the component in the larger technological system. Hence, we expect a positive effect of component diversity on component growth in the seed stage of development.

On the other hand, in the growth stage of development, the potential appeal of the component's technology to stakeholders in the wider technological environment is no longer relevant. After all, the component's stakeholders have collectively agreed upon working on the dominant subcomponent configuration, specified in the component's dominant design. This enables actor specialization and facilitates cumulative developments, hereby transforming the component's potential value into real techno-economic value. In doing so, a (broad) direction of technological development for the component has been chosen, and alternative directions (i.e., alternative subcomponent configurations) have been foreclosed. As this stage is associated with convergence towards the dominant subcomponent configuration or deep structure (see the convergence phase in Figure 4.2), diversity (i.e., divergence) implies a fragmentation of resources, hampering convergence towards the component's dominant design. As a result, it hampers the legitimation of the (dominant subcomponent configuration of the) component in the technological system, and the flow of resources that goes with it. Our next hypothesis thus is

Hypothesis 4.6: *Component diversity is positively (negatively) associated with component growth in the seed (growth) stage of development.*

4.4.2 Antecedent diversity

The technological antecedents of the component niche can be seen as the knowledge base on which the component builds, where knowledge base refers to the component's constituents (Fleming, 2001). After all, the technological antecedents are the ingredients that are used in the component's recombination process to generate the inventions contained within the technological component. The development of the technological component is to a large extent dependent on the underlying knowledge base (Duysters, 1995). Hence, the more diverse this knowledge base, the higher the recombination potential of the technological component. So, antecedent diversity yields a potential for novel combinations to emerge. We therefore expect antecedent diversity to positively impact subsequent component growth.

However, although the number of possible combinations can literally grow to infinity, given the limited number of potential components that an inventor can simultaneously consider (Fleming, 2001), it will become increasingly difficult for the involved actors to develop a sensible interpretation of all the potential novel combinations. After all, since every component can be incorporated in further re-combinations, an actor's combinatory potential (Weitzman, 1996) and associated cognitive burden (Hannan et al., 2007) grow explosively. Consequently, individuals, organizations and even entire communities cannot have more than an infinitesimal understanding of all these potential combinations and relationships. As a result, actors must focus, and recombine locally from a limited set of components and combinations, as too much diversity diminishes the likelihood that sensible meaning to novelty can be attached (Levinthal & March, 1993; Nooteboom, 2000). This implies the need for a stable or dominant subcomponent configuration (i.e., a dominant design) that enables sense-making and provides both positive heuristics that determine where to search, as well as negative heuristics that specify where not to search (Dosi, 1982).

Conversely, before a dominant subcomponent configuration or sense-making structure emerges, actors need to literally consider all potential (re-)combinations, as they can all become the basis of the future dominant design. Increasing the diversity of the knowledge base in this (seed) stage actually diminishes possibilities for sense-making and absorption, and yields high integration costs. Hence, in the seed stage of development, antecedent diversity results in a fragmentation of resources and a duplication of research efforts. Therefore, it negatively affects legitimation processes, and might even hamper the emergence of a dominant subcomponent configuration altogether. Hence, our next hypothesis becomes

Hypothesis 4.7*: Antecedent diversity is negatively (positively) associated with component growth in the seed (growth) stage of development.*

4.4.3 Descendant diversity

The technological descendants of the focal niche can be seen as the technological extensions or applications of the component's technology. In other words, the technological descendants represent the diffusion of the component's technology in the broader technological environment or landscape. The more diverse the component's technological descendants are, the more the component's technology is diffused, and the more attractive the component technology becomes for potential adopters. After all, technologies develop as they diffuse, and, as they progress, they become more attractive for potential adopters (Podolny & Stuart, 1995), offering useful and sufficient 'feedstock' for subsequent descendant technologies. Obviously, increasing the attractiveness of the technological component enhances its subsequent growth. We therefore formulate our last hypothesis as

Hypothesis 4.8*: Descendant diversity is positively associated with component growth.*

4.5 Data and methodology

Within innovation and technology studies, there is a long history of using patent data (Griliches, 1990; Jaffe, 1986; Smookler, 1966). The reason is that patent data provide an extremely useful data source, given their coverage, transparency and accessibility (Van Looy, Magerman, & Debackere, 2006). Therefore, patent data are considered by many as the most direct, detailed and objective measures of innovation (Griliches, 1981; Thoma & Torrisi, 2007). In the words of Zvi Griliches (1990: 1661), who was one of the first to study technological change empirically, "in this desert of data, patent statistics loom up as a mirage of wonderful plentitude and objectivity." Especially within biotechnology, patent statistics are a good indicator of the evolution of technology (Orsenigo et al., 2001; Powell et al., 1996).

For many 'dedicated biotechnology firms' or DBFs, a common strategy is to patent and subsequently license out or sell their technological knowledge. Large pharmaceutical firms also use patents strategically – for example, as leverage or bargaining chips in negotiations, or to stifle developments by competitors. Furthermore, since the Bayh-Doyle act – which allows the patenting of research findings funded by means of federal grants – research institutes, such as universities, are also highly active to patent their newly discovered technology. As a result, all landmark innovations within biotechnology have been patented. Therefore, many firmly believe that patent data are well suited to delineate different stages of technological evolution and the characteristics of these stages. Even though we acknowledge that patent data only represent the explicit portion of technological knowledge contained within an organization or industry, due to the importance of patents within biotechnology, it is also a fair proxy for the tacit portion of technological knowledge.

We use patent data from the United States Patent and Trademark Office (USPTO), as this is the most complete dataset for technology analysis (Podolny & Stuart, 1995). Furthermore, because the US is the largest marketplace for biotechnology, it is standard practice for non-US organizations to patent in the US (Albert et al., 1991). Additionally, because of the tight linkage between biotechnology and science, biotechnology is a relatively autonomous technology that does not primarily depend on developments within other technologies. This makes biotechnology the ideal setting for an empirical analysis of the kind that we are proposing here. Within the USPTO, biotechnology is represented by main classes 435 and 800. We define our technological components at the subclass level of biotechnology, which contains a total of 27 subclasses (i.e., 18 subclasses in class 435, and 9 subclasses in class 800), see Table 3.1.

4.5.1 Measures

Component growth, our dependent variable, is a count of the number of patents that enter our technological component in a particular month from January 1976 until December 2003. Because we have repeated observations for the same components, our data constitute a cross-sectional time-series or panel data structure. This panel is unbalanced, though, as not all niches were in existence at the start of our time window.

Regarding our density measures, System density is a count of the total number of patents (divided by 1000) contained within the domain of biotechnology (i.e., USPTO class 435 and 800) in the month prior to our dependent variable. To avoid double counting, we have subtracted focal component density. Next, Organizational density is a count of the number of organizations active in the component in the previous twelve months. Finally, focal Component density is a count of the total number of patents (divided by 1000) in the focal component in the month prior to the dependent variable, implying that this measure represents the stock of patents contained in the focal component.

Because patent citations are a fair proxy of the perceived importance of the technology in the community (Trajtenberg, 1990), these form the basis for our measure of Component status. However, because the number of citations that a component received is to a large extent dependent upon the size of the risk set (i.e., the number of inventions contained within the component or component density), we divide the number of citations by the density of the component to account for this expanding risk set (Podolny & Stuart, 1995). This implies

$$(4.1) \qquad S_{it} = \frac{\sum_{j=1}^{J} CR_{ijt}}{C_{it}}$$

where S_{it} is the status of component i at time t, CR_{ijt} is the number of citations received by invention j in component i at time t, J is the total set of inventions within component i, and C_{it} is the density of component i at time t.

Component crowding measures the extent to which a technological component builds upon the same knowledge base or antecedent technology as other components (i.e., both inside and outside our technological system). This means

$$(4.2) \qquad CC_{it} = \sum_{j=1, j\neq i}^{j=J} \sum_{k=1, k\neq i, k\neq j}^{k=K} \frac{\left|A_{ikt} \cap A_{jkt}\right|}{\left|A_{ikt}\right|}$$

where CC_{it} refers to the crowding of component i at time t, A_{ikt} to the set of technological antecedents of component i that come from component k at time t, A_{jkt} to the set of technological antecedents of component j that come from component k at time t, $|.|$ to the cardinality of a set (i.e., the number of unique elements contained within the set), ∩ to the intersection of two sets (i.e., the common elements in both sets), and both J and K to the set of all components, so both focal and non-focal components. Again, for simplicity's sake, we represent the components outside our technological system at the USPTO class level.

Component diversity represents the extent to which developments take place in subcomponents, and is measured by the distribution of patents across the component's subcomponents over the previous twelve months. Subcomponents are represented by the USPTO subclasses associated with the focal component. To measure component diversity, we will use Shannon's (1948) diversity measure, which implies

$$(4.3) \qquad D_{it} = \sum_{j=1}^{j=J} P_{ijt} \ln(1/P_{ijt})$$

where D_{it} denotes to the diversity of component i at time t, and P_{ijt} is the share of patents in subcomponent j at time t in component i, time t refers to the twelve-month period prior to the month of observation of our dependent variable, and J denotes the number of subcomponents associated with the component.

The component's Antecedent diversity is calculated over the previous twelve months according to (4.3), but now P_{ijt} refers to the share of citations made from focal component j to antecedent component i at time t. Correspondingly, the niche's Descendant diversity is calculated over the previous twelve months using (4.3), where P_{ijt} is the share of citations received from descendant component i to focal component j at time t.

Table 4.1 Definition of variables

Variable	Description
Component growth	Number of patents entering the focal component in the current month
Previous entry	Number of patents entering the focal component in the previous month divided by 1000
System density	Cumulative number of patents in the focal system in the previous month excluding component density divided by 1000
Component density	Cumulative number of patents in the focal component in the previous month divided by 1000
Organizational density	Number of organizations active in the focal component in the previous 12 months divided by 1000
Component status	Patent citations received by focal component in the previous 12 months divided by component density.
Component crowding	Component overlap between focal component and all other components in the previous 12 months divided by 1000
Component diversity	Shannon's diversity index of the distribution of patents over subcomponents in the focal component in the previous 12 months
Antecedent diversity	Shannon's diversity index of the distribution of citations made by the component to main USPTO classes in the previous 12 months
Descendant diversity	Shannon's diversity index of the distribution of citations received by the component from main USPTO classes in the previous 12 months

We also add a number of control variables. First, we include the number of previous entries and its square – Previous entry and Previous entry^2 – to allow for the estimation of dynamic models (Greene, 2003). This pair of measures effectively controls for the favorable conditions within the environment that may encourage component entry (Delacroix & Carroll, 1983; Hannan et al., 1995). We also include a number of Year dummies in all our analyses to control for year-specific effects. More specifically, we include year dummies for the years 1999 until 2003, because our analysis in the previous chapter has indicated that these years are characterized by significantly lower entry rates.
In Table 4.1, we provide an overview of the variables and their definitions. Descriptive statistics of the variables are provided in Table 4.2, and our correlation matrix is provided in Table 4.3.

Table 4.2 Descriptive statistics

Variable	mean	S.D.	min	max	25th %	50th %	75th %
Component growth	5.017	14.354	0.000	217.000	0.000	1.000	4.000
Previous entry	0.005	0.014	0.000	0.217	0.000	0.001	0.004
System density	16.554	11.166	2.879	44.954	7.701	12.551	22.606
Component density	0.669	1.628	0.001	15.139	0.022	0.085	0.571
Organizational density	0.034	0.077	0.000	0.666	0.001	0.008	0.029
Component status	0.302	0.710	0.000	20.000	0.000	0.142	0.384
Component crowding	0.077	0.059	0.000	0.306	0.029	0.079	0.113
Component diversity	1.827	1.496	0.000	4.706	0.000	1.931	3.172
Antecedent diversity	1.791	1.209	0.000	4.270	0.683	2.040	2.790
Descendant diversity	1.820	1.056	0.000	3.940	1.053	2.060	2.650

Table 4.3 Correlation matrix

	Variable	1	2	3	4	5	6	7	8	9	10
1	Component entry	1.00									
2	Previous entry	0.93	1.00								
3	System density	0.11	0.12	1.00							
4	Component density	0.88	0.88	0.10	1.00						
5	Organizational density	0.94	0.94	0.15	0.95	1.00					
6	Component status	0.01	0.00	0.17	-0.02	0.00	1.00				
7	Component crowding	-0.11	-0.11	0.25	-0.12	-0.10	0.08	1.00			
8	Component diversity	0.38	0.38	-0.08	0.48	0.46	-0.06	0.10	1.00		
9	Antecedent diversity	0.34	0.34	0.30	0.39	0.42	0.05	0.50	0.63	1.00	
10	Descendant diversity	0.29	0.29	0.34	0.36	0.37	0.06	0.44	0.55	0.84	1.00

4.5.2 Stages of evolution

To test our hypotheses, we need to conduct our analysis in two steps. That is, we first need to identify the different stages of technological development before we can actually test our hypotheses regarding the existence of different processes in these stages. As mentioned, the different stages of technological evolution are well documented in the literature. In what is considered as one of the first scientific works that treats the development of new technology as an economic phenomenon, Zvi Griliches (1957) found that the penetration of corn seeds follows a characteristics S-shaped growth pattern (i.e., Pearl Reed/Logistics curve). Since then, numerous empirical studies have contributed to establishing the S-shaped pattern as a general rule for technological growth and the diffusion of innovation (Bass, 1969; Foster, 1986; Mansfield, 1961; Pistorius & Utterback, 1997).

On the basis of this characteristics growth curve, numerous forecasting models have been developed (Young, 1993), which can be used to delineate the different stages of technological evolution. Basically, this methodology implies estimating the Logistics growth curve, and then distinguishing between the different stages using threshold values of the cumulative density function of this estimated growth curve. These so-called 'technology life cycle' or TLC models usually distinguish between four stages of technological evolution, namely the (1) seed, (2) growth, (3) maturity and (4) decline stage of development. Commonly used threshold values for the cumulative density function to distinguish between these four stages are provided in Table 4.4 below.

Table 4.4 Stages of technological evolution and threshold values of the cumulative density function (adapted from Van Looy, Debackere, Martens, & Bouwen, 2005)

Stage of evolution	Cumulative density
Seed	0.00-0.16
Growth	0.16-0.84
Maturity	0.84-0.99
Decline	0.99-1.00

Unfortunately, because most of these models rely on the cumulative density function of the Logistics distribution, they can only be used effectively when the upper limit of technological development is known (i.e., when the cumulative density is at its maximum value of 1) or when the upper limit can be estimated in a reliable way – for example, on the basis of the growth patterns of highly similar technologies. This implies that these models only have a limited applicability for completely new and emerging technologies, for which the upper limit is not known and cannot be reasonably estimated.

An alternative model that does not rely on the cumulative density function is Bass's (1969) model. This so-called rate of change model is basically an empirical version of Roger's (1962) innovation diffusion model and is one of the most widely applied models in management science (Bass, 2004). The reason is that it is associated with a simple and elegant theory that explains the existence of an empirical generalization. Interestingly, there is a striking similarity between the Bass model and the density-dependence model from organizational ecology. To be precise, both models use density to explain an empirical generalization, where the former focuses on the diffusion of technology (i.e., adoption of products and innovations), while the latter seeks to explain the evolution of organizational forms (i.e., organizational entry into and exit from organizational populations). More specifically, according to the Bass model, the probability that a technology will be initially adopted is a linear function of the number of previous adopters. The basic Bass (1969) model has the following functional form:

(4.4) $S(T) = pm + (q-p)Y(T) - q/mY^2(T)$

where the constant *p* is the coefficient of innovation (i.e., the probability of initial adoption), the constant *q* is the coefficient of imitation, the constant *m* reflects the market potential for first time adoptions, *S*(*T*) represents the predicted number of adopters at time *T*, and *Y*(*T*) is the cumulative number of previous adopters.

As mentioned, Bass's model is mainly used to study the number of initial adoptions of a technological product or invention. However, in the context of the present study, we are not so much interested in the adoption of the technology, but rather in the creation of technology (i.e., the entry of technological inventions into technological components). Therefore, we adjust the Bass model to estimate the pattern of component entry on the basis of component density. So, in the context of this study, *p* remains the coefficient of innovation, *q* remains the coefficient of imitation, the constant *m* stands for the potential for technological inventions, *S*(*T*) represents the predicted number of component entries, and *Y*(*T*) is the cumulative number of entries or component density. In estimating the parameters, *p*, *q* and *m* from discrete time series data, the following analogue can be used (Bass, 1969):

(4.5) $CE_t = \alpha + \beta C_{t-1} + \varphi C_{t-1}^2$

where CE_t represents the number of entries of inventions into our components, *a* represents *pm* in Equation (4.4), β represents (*q-p*) in Equation (4.4), φ represents $-q/m$ in Equation (4.4), and C_{t-1} is the cumulative number of entries time *t-1* (i.e., component density at *t-1*).

However, if we apply this model to the growth of our technological components, it results in a severe misspecification (i.e., many of our components cannot be estimated). This is most likely attributed to the fact that we try to apply a linear model to a count process, and we therefore use a count specific model instead. That is, the dependent variable in this model is the number of inventions that enter the technological components at a certain point in time, which is a count measure. The baseline model for analyzing count data is the Poisson distribution. After adding covariates to the distribution, this gives the Poisson regression model, which can be specified as

(4.6) $\Pr(y_t \mid x_t) = \dfrac{e^{-\lambda_t}\lambda_t^{y_t}}{y_t!}$

We then have

(4.7) $E(y_t \mid x_t) = \lambda_t = \exp(\alpha + \beta C_t + \varphi C_t^2)$

where λ_t is the deterministic function of the covariates, and C_t is component density at time *t*.

However, the restriction of applying the Poisson distribution in linear regression analysis is that, after adding covariates, the sample mean and conditional variance of the dependent variable have to be equal (Cameron & Trivedi, 1998). If this is not the case, unobserved heterogeneity results in so-called over- or underdispersion, which means that the regression model is incomplete. After all, if the model would be complete, all heterogeneity would be explained, and the condition of mean-variance equality would be met. There are several ways to account for unobserved heterogeneity. Most importantly, under- and overdispersion are dealt with in different ways. For example, underdispersion can be accounted for by applying a weighted Poisson distribution (cf. Ridout, 2004). In contrast, overdispersion is usually modeled using a negative binomial model, which basically adds a dispersion parameter to the Poisson regression model. In the previous chapter, we already established that our data suffer from overdispersion (cf. Table 3.2). Therefore, we accommodate for this by adding a dispersion parameter δ. We thus get

(4.8) $$\lambda_t' = \exp(\alpha + \beta C_t + \varphi C_t^2) \cdot \exp(\varepsilon_t) = \lambda_t \delta_t$$

The negative binomial regression model (i.e., NB2 in Cameron & Trivedi, 1998) then becomes

(4.9) $$\Pr(y_t \mid x_t, \delta_t) = \frac{e^{-\lambda_t \delta_t} (\lambda_t \delta_t)^{y_t}}{y_t\,!}$$

4.5.3 Multi-level model

Even though we most definitely acknowledge the added value of the Bass model, an important limitation is that it is a singular model that does not consider the embeddedness of technology within the environment. In other words, it does not consider the multi-level nature of technology. Therefore, we also develop an alternative model to distinguish between the different stages of technological development by explicitly taking into account the multi-level nature of technology. After all, as illustrated in the previous chapter, our technological components (e.g., recombinant DNA) do not evolve in isolation or autonomously, but do so in the context of a technological system (i.e., biotechnology as a whole). That is, components only provide the basic functionality, and interfaces and linkages are needed to allow communication between and to physically connect the component parts (Rosenkopf & Tushman, 1994). So, complementary inventions and components are necessary to unleash the full potential of the component technology. Only then is it possible to translate the basic functionality of the component into (products and processes that generate) economic value in the marketplace. And when the component generates economic value, its added value and role within the technological system become apparent. Obviously, this intensifies component development considerably. Therefore, we assume that this is the actual moment that the component enters the growth stage of development.

This naturally connects to the theory of multi-level density dependence, where processes of legitimation at the system level of analysis contribute in a positive way to component growth. Clearly, this is only the case when the component has a legitimate role in the system – i.e., when the function or added value of the component in the system is evident. Only after the components are discovered (i.e., recognized as such) and are related to one another do they comprise a technological system. That is, as components are (re-)combined with one another, and linkages and interfaces between components develop and strengthen, a system begins to form. As a result, legitimation processes start to operate at the system level, as the system as a whole starts to attract resources (e.g., venture capital, industry investment funds and institutional support) and components are legitimized within the technological system. This implies that we assume that the growth stage of a component is entered when the component is legitimized by the system – i.e., when legitimation processes at the system level (represented by system density) contribute positively to component growth.

To determine when the coefficient value of system density is consistently positive and significant, we employ a structural break model. As the name implies, a structural break model allows an investigation of whether a time series features a structural break, which means that there is a significant change in the effects of the model between two (or more) periods (Greene, 2003). The general structural break model allows for a change both in the intercept and in the slope of one or more variables. However, because we do not expect a sudden change in the intercept to occur between different stages, we do not need to allow for a change in both intercept and coefficient values. Instead, we expect a change only in the effect of system density on component growth. Our structural break model can thus be specified as

$$(4.10) \quad Y = \begin{bmatrix} S_s & 0 & X_s \\ 0 & S_g & X_g \end{bmatrix} \beta + \varepsilon$$

where Y refers to our dependent variable (i.e., component growth), S_s to system density in the seed stage, S_g to system density in the growth stage, X to variables whose coefficient values are not expected to change, β to the coefficient vector, and ε to the associated error term.

So, by estimating this structural break model for each of our technological components individually, we are able to determine at which point system density has a significant positive effect on component entry that marks the beginning of the growth stage of our components. The dependent variable for this model is component growth, as reflected by the entry of inventions into our components. Because our components are characterized by overdispersion (cf. Table 4.1), we will employ a negative binomial model. As independent variables, we have system density, which we split on a yearly basis into a before (i.e., seed) and after (i.e., growth) part to determine the location of the structural break, if present. For example, for the year 1980, we distinguish between system density before 1/1/1980 (i.e., 1976-1979) and system density after 1/1/1980 (i.e., 1980-2003), to then investigate the coefficient values of the before and after part of system density. We accept the structural break as the distinction between the seed and growth stage if (1) we find a non-significant effect for 'before system density' – that is, system density in the seed stage of development – and (2) we find a significant positive effect for 'after system density' – that is, system density in the growth stage of development. In the case of multiple valid options, we select the breakpoint with the higher Log-likelihood value (i.e., the best fitting model).

We also add several controls. First, we include the previous number of entries and its square as a control for favorable conditions (Delacroix & Carroll, 1983; Hannan et al., 1995). In other words, we use a dynamic regression model to control for unobserved heterogeneity or serial correlation. Moreover, we control for organizational and component density using the Generalized Yule specification, which means that we include the logarithmic and quadratic term of both organizational and component density as controls (cf. Chapter 3). We thus use the negative binomial model as specified in (4.9) and adjust (4.8) accordingly, which gives us

(4.11) $$\lambda_t' = \beta O_t \cdot \omega C_t \cdot \exp(\alpha + \gamma C_t^2 + \rho O_t^2 + \varsigma S_{st} + \upsilon S_{gt}) \cdot \exp(\varepsilon_t) = \lambda_t \delta_t$$

where O_t is organizational density at time t, C_t is component density at time t, S_{st} is system density in the seed stage of development at time t, and S_{gt} is system density in the growth stage of development at time t.

4.5.4 Estimation

After we have delineated the different stages of technological development for our individual components, we can continue and test our hypotheses. As we have monthly observations from 1976 to 2003 for 27 technological components, we are dealing with a cross-sectional time-series or panel data structure. When modeling panel data, there are basically two options: employing a dynamic regression model or a panel regression model. We already apply a dynamic regression model because we include the previous occurrences of our dependent variable (i.e., previous entry) in our analysis. We also employ a panel regression model, which comes in two basic flavors: (1) a fixed effects model, which adds a dummy per panel, and so effectively removes all variance between panels – this is therefore also referred to as a within-variance model; and (2) a random effects model, which assumes that heterogeneity is randomly distributed and therefore makes it possible to utilize both the within and between panel variance. More specifically, according to Hausman, Hall, and Griliches (1984), the random effects negative binomial model allows the variance of the effects to differ in the within and between dimensions, and is essentially a 'variance components' version of the negative binomial. When this random effect is drawn from Gamma distribution, mixing this a Gamma distribution with the Poisson distribution (i.e., the baseline to model count data) effectively creates a Beta distribution, with two parameters (i.e., *r* and *s*). This yields the model

$$(4.12)\quad \Pr(Y_{it} = y_{it} \mid x_{it}, \delta_i) = \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)} \left(\frac{1}{1+\delta_i}\right)^{\lambda_{it}} \left(\frac{\delta_i}{1+\delta_i}\right)^{y_{it}}$$

with

$$(4.13)\quad \lambda_{it} = \exp(x_{it}\beta + offset_{it})$$

In the random effects overdispersion model, δ_i is allowed to vary randomly across groups, and $1/(1+\delta_i) \sim \text{Beta}(r,s)$. As the name already indicates, the random effects model has the limiting assumption that the unobserved heterogeneity is randomly distributed, and therefore independent from the regressors. To determine whether this is indeed the case, we apply Hausman's specification test, which basically tests whether the coefficients from the consistent (i.e., the fixed effect) model are similar to the coefficients from the efficient (i.e., the random effects) model.

4.6 Results

In Table 4.5, we report the estimates of the Bass model to delineate the stages of development of our individual components using a negative binomial specification. According to Bass (1969), before applying estimates from a limited number of observations, the estimates should be closely examined. In doing so, a number of anomalies seem to arise. As can be seen in Table 4.5, all estimates of *a* are negative, which would implies that *pm* in (4.4) is negative, and therefore cannot be logically interpreted. However, because we are applying an exponential model instead of a linear model, the interpretation is somewhat more involved and besides the scope of the current chapter. The model does provides a rather good fit for most of our components, as can be seen by the improvement in Log-likelihood for the full model (*LL Full*) compared to the Log-likelihood of the Null model (*LL Null*) or the *Pseudo* R^2 value, and the significance of nearly all coefficient values. We therefore do use these estimates to construct the cumulative density function of our individual technological components.

In Table 4.6, we report the threshold values on the basis of the estimates from the Bass model. In column 2, the point of inflexion is calculated – i.e., the value of component density when the entry of inventions into the technological component is at its maximum and when development is halfway (i.e., the cumulative density function has a value of 0.5). Using this value, we can determine the upper limit (*L*) of component density in column 5 (i.e., when the cumulative density function is at its maximum of 1). So, on the basis of the estimates from the Bass model, we can estimate the full cumulative density function of the individual components. However, as can be seen by comparing the actual component density at December 2003 in column 7 with the theoretical maximum component density according to the Bass model (*L*) in column 2, the estimates from the Bass models appear to underestimate the maximum of component density considerable. After all, according to these estimates, biotechnology's technological components would, at this moment, all be in a mature stage of technological development, which is extremely unlikely. This finding is in line with Heeler and Hustad (1980), who report a significant underestimation of the Bass model when investigating the performance of the model for non-US data. Moreover, according to Bass (1969) himself, the model should be supplemented with additional information, and cannot be applied blindly. Hence, the Bass model does not seem to perform particularly well in our case. Notwithstanding this apparent underestimation, we do use these estimates to distinguish between the different stages, if only to provide a baseline for our multi-level model. The distinction between the different stages of development on the basis of these estimates is given in Table 4.8.

Table 4.5 Negative binomial regression estimates of Bass model for biotechnology's components

Component	α	β	φ	***LL Null***	***LL Full***	***Pseudo*** R^2
435001	-3.38***	52.81***	-178.49***	-544.48	-378.57	0.30
435002	-2.63***	27.18***	-56.02***	-650.83	-503.34	0.23
435003	-4.06***	112.10***	-1,267.23***	-267.89	-239.50	0.11
435004	-0.71***	1.79***	-0.10***	-3,060.63	-2,576.30	0.16
435005	-0.96***	1.67***	-0.12***	-3,589.61	-3,196.77	0.11
435006	-1.55***	14.90***	-13.73***	-818.23	-563.55	0.31
435007	-4.08***	63.08***	-217.32***	-479.61	-338.49	0.29
435008	-2.40***	17.12***	-21.00***	-1,208.70	-886.65	0.27
435009	-1.53***	3.87***	-0.77***	-2,525.89	-2,059.81	0.18
435010	-2.51***	21.28***	-29.56***	-828.49	-597.34	0.28
435011	-0.90***	6.72***	-2.44***	-1,235.17	-902.56	0.27
435012	-1.97***	28.38***	-72.08***	-471.44	-377.82	0.20
435013	-5.78***	430.83***	-13,230.30***	-131.83	-120.62	0.09
435014	-1.96***	5.45***	-1.63***	-2,230.51	-1,833.68	0.18
435015	-0.62***	11.33***	-11.65***	-562.52	-437.59	0.22
435016	-2.34***	6.59***	-2.67***	-1,862.30	-1,613.96	0.13
435017	-2.03***	5.61***	-1.75***	-2,272.29	-1,816.64	0.20
435018	-6.55***	556.65***	-20,671.40***	-98.51	-84.38	0.14
800001	-1.53***	71.47***	-780.08***	-139.60	-128.43	0.08
800002	-2.82***	176.79***	-3,701.94***	-98.88	-89.52	0.09
800003	-1.21***	33.14***	-100.14***	-307.82	-241.49	0.22
800004	-2.89***	116.11***	-1,208.71***	-151.45	-128.94	0.15
800005	-2.69***	39.00***	-77.98***	-607.74	-440.48	0.28
800006	-3.51***	286.64	-21,157.20	-50.69	-49.89	0.02
800007	-6.62***	1,984.18**	-230,183.00**	-33.28	-29.74	0.11
800008	-0.35***	11.50***	-11.17***	-512.13	-412.43	0.19
800009	-1.06***	12.69***	-8.20***	-721.91	-561.88	0.22

Legend: * significant at 10%; ** significant at 5%; *** significant at 1%; standard errors in brackets.

Table 4.6 Threshold values different stages of technological evolution according to estimates from the negative binomial Bass model

Component	- $\beta/(2\varphi)$	L	0.16L	0.84L	0.99L	31/12/2003
435001	148	296	47	249	293	219
435002	243	485	78	408	480	328
435003	44	88	14	74	88	74
435004	8,775	17,550	2,808	14,742	17,375	15,239
435005	6,866	13,731	2,197	11,534	13,594	10,983
435006	543	1,086	174	912	1,075	829
435007	145	290	46	244	287	164
435008	408	815	130	685	807	667
435009	2,503	5,007	801	4,206	4,957	3,698
435010	360	720	115	605	713	486
435011	1,375	2,750	440	2,310	2,722	2,253
435012	197	394	63	331	390	291
435013	16	33	5	27	32	30
435014	1,671	3,342	535	2,807	3,308	2,388
435015	486	973	156	817	963	727
435016	1,236	2,471	395	2,076	2,447	1,346
435017	1,601	3,203	512	2,690	3,171	2,187
435018	13	27	4	23	27	19
800001	46	92	15	77	91	80
800002	24	48	8	40	47	38
800003	165	331	53	278	328	168
800004	48	96	15	81	95	66
800005	250	500	80	420	495	436
800006	7	14	2	11	13	14
800007	4	9	1	7	9	8
800008	515	1,030	165	865	1,019	818
800009	773	1,547	247	1,299	1,531	1,306

In Table 4.7, we provide the estimates of our multi-level structural break model on the basis of the effect of system density on component entry. To reiterate, to distinguish between the seed and growth stage of development, we select a certain point in time (i.e., a certain year) as composing a structural break if (1) we find a non-significant effect for system density in the seed stage of development, and (2) we find a significant positive effect for system density in the growth stage of development. Moreover, if multiple candidate structural break points are found, we select the point that provides the best model fit (i.e., with the highest Log-likelihood value). As can be seen from Table 4.7, 13 out of a total of 27 components enter the growth stage during our period of observation. All of these 13 components demonstrate significant model improvements when using the suggested structural break point. The improvement in model fit can be determined by comparing two times the difference in the Log-likelihood to a χ^2 distribution with one degree of freedom (column 8 of Table 4.7). Even though component 800001 does not show a significant coefficient value for community density in the growth stage of development (i.e., S_g in Table 4.7), we do use the time of the break in our subsequent analysis. The reason is that the coefficient value is consistently positive after its structural break point and the model improvement is significant (i.e., $p < 0.05$).

Table 4.7 Negative binomial regression estimates of multi-level structural break model of biotechnology's components

Component	S	LL Base	Growth	S_s	S_g	LL ML	χ^2
435001	0.271***	-298.91	1/1987	0.100	0.292***	-292.75	12.32***
435002	0.464***	-368.42	1/1976	n.a.	n.a.	n.a.	n.a.
435003	-0.053	-137.24	n.a.	n.a.	n.a.	n.a.	n.a.
435004	0.063	-1,202.77	1/1979	0.067	0.142***	-1,199.34	6.86***
435005	0.385***	-1,123.33	1/1976	n.a.	n.a.	n.a.	n.a.
435006	0.098***	-482.18	1/1981	-0.167	0.130***	-478.74	6.88***
435007	0.181***	-216.34	1/1986	0.063	0.246***	-213.91	4.86**
435008	-0.083**	-553.06	n.a.	n.a.	n.a.	n.a.	n.a.
435009	0.295***	-868.42	1/1976	n.a.	n.a.	n.a.	n.a.
435010	0.305***	-437.80	1/1976	n.a.	n.a.	n.a.	n.a.
435011	0.117	-670.91	1/1984	0.109	0.189***	-668.58	4.66**
435012	0.134**	-356.59	1/1984	0.029	0.185***	-354.16	4.86**
435013	0.033	-46.67	n.a.	n.a.	n.a.	n.a.	n.a.
435014	0.002	-743.54	n.a.	n.a.	n.a.	n.a.	n.a.
435015	0.214***	-420.27	1/1984	n.a.	n.a.	n.a.	n.a.
435016	0.081	-583.04	1/1976	n.a.	n.a.	n.a.	n.a.
435017	-0.013	-751.86	n.a.	n.a.	n.a.	n.a.	n.a.
435018	0.485***	-55.19	1/1990	0.169	0.438***	-52.63	5.12**
800001	0.347	-116.09	1/1996	-0.769	0.101	-113.17	5.84**
800002	0.848***	-78.29	1/1991	n.a.	n.a.	n.a.	n.a.
800003	0.290***	-211.29	1/1992	-0.818	0.295***	-208.82	4.94**
800004	0.180***	-124.32	1/1991	0.022	0.380***	-118.3	12.04***
800005	0.099*	-402.28	1/1996	0.062	0.902**	-398.92	6.72***
800006	1.193***	-40.97	1/1988	-0.592	1.067***	-39.2	3.54*
800007	0.051	-28.99	n.a.	n.a.	n.a.	n.a.	n.a.
800008	0.060	-363.91	n.a.	n.a.	n.a.	n.a.	n.a.
800009	0.083	-471.99	1/1986	-0.082	0.162**	-468.06	7.86***

Legend: * significant at 10%; ** significant at 5%; *** significant at 1%; standard errors in brackets; S = system density; S_s = system density in the seed stage of development; S_g = system density in the growth stage of development; *LL* = Log likelihood; *Base* = comparison model; *ML* = multi-level structural break model; *Growth* = month of start growth stage component; χ^2 = Chi square value of multi-level model = -2 * (*LL Base* – *LL ML*).

For the remaining components, we did not find a structural break on the basis of our criteria or algorithm. This implies that these components are in the same stage of development for the whole period of observation. The question then becomes whether they are in the seed or growth stage of development during our period of observation. Again, on the basis of the effect of system density on component entry, we can determine the appropriate stage. Our findings are reported in column 4 of Table 4.7. As can be seen in column 3, components 435002, 435005, 435009, 435010, 435015, 435016 and 800002 are assumed to be in the growth stage from the start of our observation period. After all, with the exception of component 435016, the effect of system density on component growth is significantly positive. The reason that we assume that component 435016 is in the growth stage of development is that (1) the effect of system density on component growth is consistently positive, (2) the mean of component entry is 2.74, which is the 10th highest of all components, and (3) maximum component entry is 14 components per month, which is 12th highest of all components. The other components (i.e., components 435003, 435008, 435013, 435014, 435017, 800007, and 800008) are assumed to be in the seed or formative stage during the observation period.

In Table 4.8, we juxtapose the start dates of the growth stage according to the adjusted Bass and multi-level models. Moreover, in column 4, we also include a model that distinguishes between the seed and growth stage of development using a process of random assignment (i.e., by randomly selecting the period in which the component enters the growth stage) as a baseline model to determine the performance of the adjusted Bass and multi-level models. According to the adjusted Bass model, at the end of the observation period (i.e., 31/12/2003), all components are in a growth stage of development, which would imply biotechnology as a whole to be in a growth stage of development as well (to be precise, as of January 1998, the date when the final component enters the growth stage of development). In contrast, our multilevel model assumes that seven components are still in a formative stage of development, implying biotechnology as w whole to be in the formative seed stage of development at the end of our observation period. Hence, on the basis of our discussion in Paragraph 2, we can already conclude that our multilevel model better represents the evolution of biotechnology.

We still compare the performance of our different models empirically. To do so, we combine our technological components (or individual panels) into one analysis for two reasons. First, otherwise we do not have enough observations when we add our substantive variables. Second, as mentioned, we do not aim to explain the pattern of evolution of individual components, but rather to develop a formal systemic model. In Table 4.9, we report the results of our analysis of the alternative structural break models (i.e., according to the distinction between the stages of development according to Table 4.8). We want to make the following observations. First of all, the pattern of findings for the different models is highly similar, with little difference in significance levels and model fit. However, this is mainly a reflection of the temporal structure of our models. After all, the seed period is always situated at the start of the period and the growth period is always situated at the end. This has important implications for the distinctiveness of these models. For example, from the 8,021 observations in total, the overlap in observation between the Bass model and Random Assignment model is 4,611 in the seed period and 1,627 in the growth period. This means that only 1,783 observations are actually assigned to different periods by the two models, and that 6,238 out of a total of 8,021 observations overlap – i.e., roughly 78%. This illustrates that it should be no surprise that the models appear to have little distinguishing power according to the small difference in Log-likelihood values of the models.

Table 4.8 Start date of growth stage according to different models

Component	Bass model	Multi-level model	Random assignment model
435001	1/1990	1/1987	08/1976
435002	1/1984	1/1976	03/1986
435003	1/1976	n.a.	1/1978
435004	2/1990	1/1979	2/1987
435005	11/1976	1/1976	10/1977
435006	9/1995	1/1981	8/1993
435007	8/1988	1/1986	3/2001
435008	7/1977	n.a.	3/1984
435009	1/1976	1/1976	11/1994
435010	2/1988	1/1976	6/1996
435011	9/1995	1/1984	12/2002
435012	7/1991	1/1984	9/2001
435013	1/1976	n.a.	7/1989
435014	1/1976	n.a.	10/2000
435015	2/1995	1/1984	8/1982
435016	1/1976	1/1976	4/1985
435017	1/1976	n.a.	9/2003
435018	1/1976	1/1990	10/1988
800001	9/1997	1/1996	6/1985
800002	1/1997	1/1991	10/1997
800003	1/1998	1/1992	3/1980
800004	1/1996	1/1991	8/1995
800005	9/1993	1/1996	6/2000
800006	6/1988	1/1988	10/1997
800007	1/1976	n.a.	12/1988
800008	6/1997	n.a.	9/1987
800009	11/1997	1/1986	6/1995

The Log-Likelihood value of the baseline model (i.e., without a structural break for all our components) is 11,582 with 18 degrees of freedom (not reported here, for the sake of brevity: available upon request). This implies that all models (i.e., adjusted Bass, multi-level, and random assignment) provide a significantly better fit than the baseline model. After all, as can be seen in Table 4.9, the worst fitting model (i.e., the random assignment model in column 4) already improves model fit significantly (i.e., a χ^2 value of 82 with 7 degrees of freedom means that $p < 0.01$).

As can be seen in Table 4.9, our multi-level model provides for the best fit (Log-likelihood value of 11,522). Furthermore, even though the different models assign many observations to the same stage, the observations that do differ with respect to the stage to which they are assigned do make for a big difference for some variables. Especially with respect to diversity and antecedent diversity, some interesting distinctions between our multi-level model and the alternative specifications become apparent. For example, diversity has a significant negative effect in both stages of development in all but our multi-level model, where it is not significant and even positive in the seed stage. With respect to antecedent diversity, in our multi-level model it has a significant negative effect, while the other models do not support this finding. This illustrates the importance of correctly specifying the model to be estimated, as a small difference can have dramatic implications.

However, we do have to note that due to the specifications of structural break models, correlations between variables are substantially amplified (due to the great number of zero values), implying that problems of multicollinearity arise. We therefore do not draw strong conclusions from the coefficient values of our measures from these models. However, because multicollinearity has no effect on model fit, we are completely confident that our multi-level model provides a better fit. Before we continue with this analysis, though, we first have a look at the confidence interval of our dependent variable (i.e., component entry) to determine whether the different stages of technological development are indeed different.

As can be seen in Table 4.10, the mean count of patents that enter our technological components (entry) in the growth stage is significantly higher than in the seed stage of development. However, this is rather obvious because the seed stage is temporally positioned before the growth stage and the entry of inventions increases over time. So, this does not say much about the quality of the structural break according to our multi-level model. However, as can be seen in Table 4.10, the growth rate (i.e., growth = entry/density) is also significantly higher in the growth stage. So, it appears that the distinction between the different stages of technological development is a substantive rather than a spurious one. Therefore, we proceed with this distinction in our subsequent analysis. More specifically, we estimate two negative binomial random-effects panel models, namely one for the seed period and one for the growth period, to prevent possible multicollinearity issues that would result from a structural break model. In Tables 4.11 and 4.12, we report the estimates of these models.

To get a clear picture of the effects of status and crowding, we first estimate a model without the interaction term between crowding and status, and without antecedent and descendant diversity. This model is displayed in column 2 of Tables 4.11 and 4.12. Next, we add the interaction term between component crowding and component status in column 3. Finally, in column 4, we also add our measures of antecedent and descendant diversity.

Table 4.9 Negative binomial dynamic panel regression estimates of alternative structural break models

	Bass model	Multi-level	Random
Previous entry	8.127***	6.971***	7.556***
	[1.057]	[1.048]	[1.069]
Previous entry	-23.906***	-19.153***	-21.214***
	[4.798]	[4.763]	[4.849]
LN(Organizational density*1000)	0.558***	0.536***	0.572***
	[0.032]	[0.033]	[0.033]
Organizational density^2	-0.397	-0.482*	-0.559**
	[0.264]	[0.263]	[0.264]
LN(Component density*1000)	0.290***	0.299***	0.297***
	[0.035]	[0.030]	[0.030]
Component^2	0.353	0.522	0.58
	[0.499]	[0.499]	[0.511]
Seed(System density)	0.023***	0.020***	0.016***
	[0.007]	[0.004]	[0.004]
Growth(System density)	0.015***	0.021***	0.019***
	[0.003]	[0.003]	[0.003]
Seed(Component status (CS))	0.156***	0.133***	0.204***
	[0.028]	[0.043]	[0.035]
Growth (Component status (CS))	0.346***	0.248***	0.209***
	[0.036]	[0.018]	[0.019]
Seed (Component crowding (CC))	0.161	-0.004	0.621
	[0.596]	[0.967]	[0.529]
Growth (Component crowding (CC))	0.044	0.426	0.007
	[0.466]	[0.399]	[0.441]
Interaction: Pre(CS) * Pre(CC)	2.707	-160.312**	-130.392**
	[80.335]	[81.074]	[61.717]
Interaction: Post(CS) * Post(CC)	-244.537***	-263.771***	-261.787***
	[53.657]	[57.480]	[60.569]
Seed (Component diversity)	-0.149***	0.099	-0.137***
	[0.051]	[0.064]	[0.050]
Growth (Component diversity)	-0.079*	-0.07	-0.094**
	[0.047]	[0.044]	[0.044]
Seed (Antecedent diversity)	-0.059	-0.226***	-0.021
	[0.053]	[0.064]	[0.042]
Growth (Antecedent diversity)	-0.043	-0.015	-0.076**
	[0.034]	[0.035]	[0.039]
Seed (Descendant diversity)	0.180***	0.154**	0.154***
	[0.062]	[0.065]	[0.050]
Growth (Descendant diversity)	0.160***	0.172***	0.184***
	[0.039]	[0.041]	[0.043]
Constant	-2.140***	-2.295***	-2.197***
	[0.144]	[0.137]	[0.131]
Observations	8021	8021	8021
Number of components	27	27	27
Degrees of freedom	25	25	25
r	8.342	9.103	8.394
s	3.826	4.233	3.942
LL Constant	-14,582	-14,582	-14,582
LL Comparison	-11,736	-11,758	-11,773
LL Full model	-11,530	-11,522	-11,541

Legend: * significant at 10%; ** significant at 5%; *** significant at 1%; standard errors in brackets.

Table 4.10 Confidence interval for entry and growth in different stages of technological development

Variable	Obs.	Mean	S.E.	95% confidence interval	
Growth (seed)	2996	0.0082	0.0008	0.0067	0.0097
Growth (growth)	5052	0.0131	0.0008	0.0115	0.0146
Entry (seed)	2996	1.8435	0.0623	1.7214	1.9655
Entry (growth)	5052	6.8804	0.2481	6.3941	7.3668

The first observation relates to the difference with the estimates from the structural break model. However, this is not alarming for two reasons. First, as mentioned, due to the large amount of zeros in the structural break models, multicollinearity among our measures increases considerably, which potentially distorts the results. Second, because we estimate separate models for the different periods in our final analysis (cf. Table 4.11 and 4.12), the coefficient variables for our remaining variables (e.g., previous entries, organizational density, and niche density) and the constant term are also allowed to vary, which basically results in completely different models altogether. Therefore, comparing these models is virtually a senseless exercise. For both stages, the complete model (i.e., *Seed 3* and *Growth 3*) provides the better fit. We therefore use these models for reporting our results.

Furthermore, we have performed Hausman's specification test to determine whether the random effects specification is indeed appropriate. Hausman's test indicates whether the coefficient estimates of the fixed effects (i.e., consistent) model are significantly different from the coefficient estimates of the random effects (i.e., efficient) model. If these coefficient values are not significantly different, this illustrates that the independent variables are not correlated with the random disturbance term, and that this model can indeed be appropriately applied. The results of Hausman's specification test both for model Seed 3 and Growth 3 indicate that the random effects specification is indeed appropriate (not reported here, for the sake of brevity: available upon request). Next, we discuss the implications for our hypotheses.

According to Hypothesis 4.1, system density is positively associated with component entry in the growth stage of development. Notwithstanding the fact that our estimates clearly seem to support this hypothesis, we cannot confirm this hypothesis. After all, we have used system density to distinguish between the different stages of development in the first place, so these findings are merely the result of our initial assumptions. As a result, we cannot directly confirm this hypothesis. However, indirectly, the pattern of findings (especially component diversity and antecedent diversity) seems to suggest that the distinction between stages on the basis of the effect of system density is indeed justifiable. In the growth stage of development, increasing the value of system density with one standard deviation increases the rate of entry with 44%.

Table 4.11 Negative binomial dynamic multi-level panel regression estimates of the seed stage of technological evolution

	Seed 1	***Seed 2***	***Seed 3***
Previous entry	35.136**	35.218**	33.287**
	[13.888]	[13.905]	[13.896]
Previous entry^2	-952.06	-1,014.65	-999.172
	[662.814]	[664.760]	[663.722]
LN(Organizational density*1000)	0.510***	0.522***	0.619***
	[0.069]	[0.069]	[0.071]
Organizational density^2	-7.216	-7.097	-17.313
	[10.410]	[10.368]	[10.626]
System density	0.005	-0.001	0.004
	[0.006]	[0.006]	[0.007]
LN(Component density*1000)	0.284***	0.295***	0.289***
	[0.064]	[0.064]	[0.065]
Component density^2	56.778*	70.859**	59.896*
	[32.858]	[33.227]	[33.766]
Component diversity	0.325***	0.299***	0.346***
	[0.107]	[0.105]	[0.102]
Component status (CS)	0.181***	0.055	0.066
	[0.038]	[0.091]	[0.087]
Component crowding (CC)	-1.036	-2.318**	-1.63
	[1.080]	[1.142]	[1.155]
Interaction: CS * CC		4.033***	4.175***
		[1.197]	[1.160]
Antecedent diversity			-0.312***
			[0.067]
Descendant diversity			0.167**
			[0.066]
Constant	-2.208***	-2.104***	-2.154***
	[0.248]	[0.247]	[0.246]
Observations	2976	2976	2976
Number of components	20	20	20
Degrees of freedom	15	16	18
r	29.788	31.653	41.419
s	8.058	8.59	11.095
LL Constant	-3,584	-3,584	-3,584
LL Comparison	-3,107	-3,103	-3,073
LL Full model	-3,077	-3,069	-3,058

Legend: * significant at 10%; ** significant at 5%; *** significant at 1%; standard errors in brackets.

Hypothesis 4.2 posits that, due to positive spillovers, component density is positively associated with component growth in both stages of technological development, and that this effect is not significantly weaker in the growth stage of development. We find strong support for this hypothesis. In the seed (growth) stage of development, moving niche density from its 1st quartile to its 3rd quartile increases niche entry with 22% (21%). To determine whether the effect of density is significantly weaker in the growth stage of development, we have estimated (not reported here; available upon request) a structural break model following (4.10) where component density was split into its seed and growth part. According to this analysis, the effect of component density is not significantly lower in the growth stage of development, providing support for our hypothesis.

Table 4.12 Negative binomial dynamic multi-level panel regression estimates of the growth stage of technological evolution

	Growth 1	***Growth 2***	***Growth 3***
Previous entry	6.887***	6.806***	7.156***
	[1.128]	[1.130]	[1.146]
Previous entry^2	-18.860***	-18.552***	-19.662***
	[5.113]	[5.117]	[5.180]
LN(Organizational density*1000)	0.499***	0.497***	0.480***
	[0.040]	[0.040]	[0.043]
Organizational density^2	-0.712**	-0.724***	-0.551*
	[0.278]	[0.278]	[0.283]
System density	0.037***	0.038***	0.032***
	[0.003]	[0.003]	[0.004]
LN(Component density*1000)	0.265***	0.267***	0.239***
	[0.034]	[0.034]	[0.036]
Component density^2	1.424***	1.453***	0.906
	[0.535]	[0.535]	[0.555]
Component diversity	-0.105**	-0.104**	-0.126***
	[0.046]	[0.046]	[0.048]
Component status (CS)	0.207***	0.220***	0.220***
	[0.021]	[0.020]	[0.020]
Component crowding(CC)	-0.261	0.067	-0.283
	[0.399]	[0.448]	[0.465]
Interaction: CS * CC		-0.58	-0.383
		[0.367]	[0.373]
Antecedent diversity			0.026
			[0.036]
Descendant diversity			0.152***
			[0.043]
Constant	-1.957***	-1.996***	-1.999***
	[0.160]	[0.163]	[0.165]
Observations	5045	5045	5045
Number of components	20	20	20
Degrees of freedom	15	16	18
r	7.102	7.18	6.682
s	3.654	3.704	3.439
LL Constant	-10,413	-10,413	-10,413
LL Comparison	-8,633	-8,633	-8,609
LL Full model	-8,426	-8,425	-8,417

Legend: * significant at 10%; ** significant at 5%; *** significant at 1%; standard errors in brackets.

Hypothesis 4.3 states that the number of organizations that adopt the technological component is a proxy for the legitimation of technology. Because legitimation processes are more important in the formative (seed) stage of development, a stronger positive effect is expected in this stage. Our estimates provide some, but no full support for this hypothesis. We do find a stronger effect for the linear term of organizational density in the seed stage of development, and the quadratic term becomes significantly negative in the growth stage of development (cf. Table 4.11 and 4.12). So, the effect of organizational density is stronger in the seed stage than in the growth stage. However, additional analyses (not reported here, for the sake of brevity; available upon request) do not reveal a significant difference in the two functions. Even though the coefficients are not significantly different, the difference in effects is rather large. Moving organizational density from the 1st quartile to the 2nd quartile in the seed stage of development, increases component growth with 171%, compared to 77% in the growth stage. Moreover, moving organizational density from its median value to the 3rd quartile increases component growth with 245% in the seed stage of development, and increases component growth with 89% in the growth stage of development.

Hypothesis 4.4 claims that, due to the inherent uncertainty of biotechnology developments during our period of observation, component status is positively associated with component growth in both stages of development. Due to a much higher level of uncertainty in the seed stage of development, the effect is expected to be stronger in the seed stage vis-à-vis the growth stage of development. Only the first part of this hypothesis is confirmed by our estimates. As can be seen in models *Seed 1* and *Growth 1* in Table 4.11 and Table 4.12, the effect of status is positive and significant in both stages of development. However, contrary to our expectations, the effect appears to be somewhat stronger in the growth stage of development. Comparison of the confidence intervals reveals that the effect is not significantly different (i.e., the 95% confidence interval of status is [0.11-0.26] in the seed stage of development, and [0.17-0.25] in the growth stage of development). Regarding the size of the effect, in the seed (growth) stage of development, moving from the 1st quartile to the median value increases component entry with 2.6% (2.97%), while further increasing the value of component status from its median value to the 3rd quartile further decreases entry with another 4.48% (5.14%).

According to Hypothesis 4.5, component crowding is positively (negatively) associated with component growth in the seed (growth) stage of development. In accordance with Chapter 3, we do not find a significant effect for the traditional measure of component crowding. In interaction with status, according to model *Seed 2*, the main effect of niche crowding is significantly negative in the seed stage of development. However, this negative effect disappears when we add antecedent and descendant diversity in model *Seed 3*, which leaves only the positive interaction term. This provides some support for the first part of our hypothesis. Obviously, we cannot draw any strong conclusion about the effect of component crowding in the different stages of development.

Hypothesis 4.6 argues that niche diversity is positively (negatively) associated with component entry in the seed (growth) stage of development. This hypothesis is fully confirmed by our estimates. In the seed (growth) stage of development, a standard deviation increase in niche diversity increases (decreases) niche entry with 66% (17%).

Hypothesis 4.7 states that antecedent diversity is negatively (positively) associated with component entry in the seed (growth) stage of technological development. We only find partial support for this hypothesis. On the one hand, even though the effect of antecedent diversity is positive in the growth stage of development, this effect is non-significant. On the other hand, antecedent diversity does have a significant negative effect on component growth in the seed stage, and increasing antecedent diversity with one standard deviation decreases component entry with 35%. We also find that the coefficients of antecedent diversity are significantly different in the two stages of development. The confidence interval of antecedent diversity is [-0.44, -0.18] in the seed stage of development, and [-0.04, 0.10] in the growth stage of development.

Finally, Hypothesis 4.8, which postulates that descendant diversity has a positive effect in both stages of development, can also be confirmed by our estimates. Increasing the value of descendant diversity with one standard deviation in the seed (growth) stage of development, increases niche entry with 23% (14%). Further analysis indicates that there is no significant difference in the coefficient value for descendant diversity in the two stages of development. The 95% confidence interval for descendant diversity is [0.04, 0.30] in the seed stage of development, and [0.07, 0.24] in the growth stage of development.

4.7 Discussion and conclusion

Overall, our estimates generate broad support for many of our hypotheses (see Table 4.13), providing evidence for our claim that there are indeed different stages of technological evolution. This allows us to move beyond a mere caricature of technological evolution as an S-shaped growth pattern, and enables an investigation into the processes that underlie this characteristic growth pattern. Our estimates reveal an intricate, but characteristic pattern of technological evolution, with different processes operating at different stages of development and at different levels of analysis. Obviously, this is not a surprising observation, as it is well documented that technological change is a highly complex, dynamic, and inherently multi-level phenomenon (Tushman & Nelson, 1990). Even though it is impossible to draw strong conclusions and implications on the basis of a single study, our pattern of significant findings (both in this chapter, as well as in the previous chapter) does demonstrate that further investigation is certainly warranted. Not only to further refine our theory, but also to validate our findings in other settings (e.g., for more mature technologies). Below, we provide some directions for future research and delineate the boundaries of our current investigation.

Table 4.13 Overview of hypotheses and results

Hypothesis		Expected Seed	Expected Growth	Found Seed	Found Growth
4.1	System density		↑		↑
4.2	Organizational density	↑↑	↑	↑***	↑***
4.3	Component density	↑	↑	↑***	↑***
4.4	Component status	↑	↑	↑***	↑***
4.5	Component crowding	↑	↓	↑	↓
4.6	Component diversity	↑	↓	↑***	↓***
4.7	Antecedent diversity	↓	↑	↓***	↑
4.8	Descendant diversity	↑	↑	↑***	↑***

Legend: * significant at 10%; ** significant at 5%; *** significant at 1%; standard errors in brackets.

First, by conceiving of technology as a system composed of a set of interdependent components that evolve through different stages of technological development, we have effectively created a multi-level and systemic evolutionary model of technological growth. Our analysis demonstrates that this model is better suited for studying the growth of emerging technologies than the singular (adjusted) Bass model, which signifies the importance of considering the embeddedness of technology when considering its growth or evolution. According to our model, when a component develops a stable role within a technological system (i.e., after a dominant subcomponent configuration is established), it begins to form an integral part of that system, and the processes that direct the component's growth and evolution change.

On the one hand, before this dominant subcomponent configuration (i.e., in the seed stage of development), focal diversity has a positive effect on component growth. Hence, alternative subcomponent configurations attract resources and attention to further the development of this array of alternative technological structures (or technological options). However, despite the advantageous effect of alternative technological structures (i.e., subcomponent configurations), these alternative configurations should not be based upon diverse technological knowledge, which is indicated by the negative effect of antecedent diversity in this stage. That is, due to the lack of a dominant design, diverse knowledge reduces the sense-making capabilities and increases integration costs.

On the other hand, after a dominant design has been established, the component is legitimated at the system level, which means that it now forms an integral part of the system's structure. This means that alternative subcomponent configurations (i.e., indicated by component diversity) thwart resources and attention from the agreed-upon dominant subcomponent configuration, which hampers technological growth. Moreover, because the dominant design provides a means to make sense of the environment, knowledge-base diversity no longer has a negative effect on technological growth. The dominant subcomponent configuration (i.e., a dominant design) acts as some sort of filter or heuristic, which not only redirects resources and attention in the technological environment, but also acts as a sense-making structure with which to interpret the environment. Hence, stability is needed to make sense of the world, hereby reducing uncertainty, enabling specialization, and facilitating cumulative changes.

When taking this previous argument to a higher level of aggregation, after each component is identified and has established a stable role within the technological system, the system itself becomes a stable and predictable integrated whole, and enters the growth stage of development. That is, the system has formed a dominant component configuration, or a dominant system design. In other words, stability travels upward. This connects to Barley's (1990) finding that technology-induced micro-social dynamics travel upwards in an orderly manner. By explicating how this stability develops from the bottom up, it is possible to elucidate the emergence of structures at higher levels of analysis. Furthermore, the model proposed here can be easily extended to include multiple levels of analysis. Then, it can allow for fine-grained analyses of technological systems and subsystems. For example, it is possible to conceive inventions bundled into components, components bundled into products and processes, and products and processes bundled into paradigms. Within such a hierarchically nested multi-level model, levels are nested within one another, and wholes are composed of elements at lower levels, which are themselves part of more extensive wholes (Baum, 1999). Indeed, more and more work recognizes the value added of paying explicit attention to the nested nature of multiple levels of analysis (Baum & Singh, 1994a). By investigating the formation of these stable configurations or structures at multiple levels of analysis, we can develop greater insight into the path-dependent nature of technology, and draw important managerial and policy implications. Obviously, our work here implies only an initial first step, and much work needs to be done to develop a solid foundation for the development of such a hierarchically nested, multi-level model of technology.

Even though, on the basis of our finding in this chapter, we can provide some initial points of advice. The fact that diversity is positive in seed stages implies that policy and management should stimulate many alternatives in the initial stages of technological evolution. However, after the emergence of a dominant design, it is important to stop exploring and/or supporting alternatives, and instead focus on developing the dominant configuration that has been created. Hence, now, alternative programs could be terminated and resources could be redirected into developing the dominant technological design configuration.

Second, the current literature on technology and innovation treats the origins of novelty as exogenous and random, and focuses mainly on processes of diffusion and absorption (Fleming, 2001; Gilsing & Nooteboom, 2006). In contrast, in the current study, by distinguishing between the seed and growth stage of development, separated by a dominant design, we focus on both the process of knowledge creation and the process of knowledge diffusion. On the one hand, the seed stage of development can be characterized by the (social) construction of a dominant design, in which the basic or dominant structure of the technological component is created. On the other hand, in the growth stage of technological development, a dominant design exists that outlines the basic structure of the component and directs its future growth, development and evolution. So, the growth stage can be characterized as technologically deterministic, where the dominant design of the technology diffuses throughout the environment, and the actors and stakeholders in the environment adjust their structures and procedures to facilitate the development of the agreed upon dominant design configuration of the technological component. As such, our systemic multi-level evolutionary model enables an analysis of both the process of knowledge creation and the subsequent diffusion of the created knowledge.

Third, by further taking into account the lineage of technology, we have added two additional dimensions to the technological niche, namely antecedent and descendant diversity. In doing so, we found that the embeddedness of a niche (i.e., how it relates to other technological niches) has a substantial effect on its growth rate, illustrating the importance of a socialized perspective towards technological change. Both sides of a niche's technological lineage, namely the diversity of its antecedent technologies and of its descendant technologies, have a strong effect on the focal niche's growth rate. As illustrated above, this has generated more insight into the twin processes of knowledge creation and diffusion, characterized by the different stages of technological development. Even though we have demonstrated the significance of the diversity of these dimensions of the technological component, it is also possible to conceive of other characteristics of these dimensions. For example, results from some preliminary analyses (available upon request) indeed indicate that antecedent and descendant stability also play an important role in the evolution and growth of technology. A thorough investigation of the effect of different characteristics of antecedent and descendant technology on technological development would surely contribute much to our understanding of the growth and evolution of technology.

Fourth, to concentrate our attention on the evolution of technology, we have largely abstracted from the role of the organization. Obviously, the insights from this analysis should be integrated with extant knowledge about organizational evolution, first by means of theoretical exploration, and subsequently by means of empirical investigation. Here, we have opened the door to a plethora of highly interesting research questions that can be further developed and explored. More specifically, by providing a quantitative model that facilitates a distinction between different stages of technological evolution, it becomes possible to explore the consequence of these different stages for individual organizations, by examining the position of organizations within a technological component at different stages of development, and by relating this position to organizational performance and survival. Clearly, the stages of technological development can also be considered in unison with the technology strategy of the organization. For example, we can consider an organization’s technology strategy or search behavior (i.e., divergence or technological exploration and convergence or technological exploitation) in different stages of technological development along the lines suggested in Figure 4.3.

Technology \ Organization's strategy	Divergence	Convergence
Divergence	Support alternative design configurations	Support single design configuration
Convergence	Challenge dominant design configuration	Develop dominant design configuration

Figure 4.3 The organization’s strategy and stages of technological development

In the seed stage of technological divergence, due to the existence of alternative design configurations, the organization has two options. First, it can support alternative design configurations to guarantee that the organization will have a stake in the future dominant design configuration (i.e., applying a hedging strategy). Second, the organization can concentrate its attention by supporting one single design configurations under the expectation that this will become the future dominant design configuration (i.e., applying a strategy of placing all eggs in one basket). In the growth stage of technological convergence, a dominant design configuration does exist and the organization again has two options. First, it can work on alternative design configurations in an effort to overthrow the ‘current’ dominant design configuration. Alternatively, it can contribute to the development of (a part of) the dominant design configuration. Obviously, a mixture between strategies is also possible.

At higher levels of analyses (i.e., at the level of an organizational population and community), we can relate the different stages of technological development to the processes of entry and exit of organizations and organizational forms. This would be an important contribution to the literature. After all, even though it is widely acknowledged that technology drives ecological processes, in population ecology, with few exceptions, connections between technological change and organizational evolution are not of central interest (Baum et al., 1995). Moreover, a formal model of the evolution of technology would allow a systematic investigation into the co-evolution of technologies and organizations, a phenomenon that is recognized by many as being highly important (Anderson & Tushman, 1990; Barnett, 1990; Baum et al., 1995; Dosi, 1984; Nelson & Winter, 1982; Tushman & Anderson, 1986; Utterback & Suárez, 1993). After all, even though technology is structured (mainly) by organizations (i.e., through the creation of a dominant design), technology subsequently structures organizations (i.e., after a dominant design has been established). Hence, technological growth is highly path dependent. So, technology not only liberates us, but also entraps us (Winter, 2008). Hence, it is clear that technological change deserves a central role in any organization theory (Tushman & Nelson, 1990). In the remainder of this thesis, we therefore investigate further how these different stages affect organizational performance.

Part III Organization

"Organizations have to have continuity, and yet if there is not enough new challenge, not enough change, they become empty bureaucracies, awfully fast. "

~ *Peter F. Drucker*

Chapter 5

A Logical Formalization of the Theory of the Technological Niche

5.1 Introduction

In the previous two chapters, we have defined the technological niche at the level of a technological domain, to elucidate aggregate patterns of technological development. In so doing, we have developed insights that have important implications for individual organizations. However, before we can move to the organization-level analysis, we first need to define the technological niche at the organizational level. As mentioned previously, Podolny, Stuart, and Hannan (1996) have already defined the technological niche at the level of an individual organization. Hence, their work provides a natural starting point for our endeavors. It might have become clear by now that Podolny, Stuart, and Hannan (1996) define two dimensions for the organization-specific technological niche, namely technological crowding and technological status.

Their technological crowding argument builds upon the general notion that the intensity of the competitive pressure exerted by one entity on another is proportional to niche overlap (Hannan & Freeman, 1989; MacArthur, 1972).[15] Because technology constitutes a core feature of the organization (Hannan & Freeman, 1984), technological crowding (i.e., overlap of an organizations' technological niche) increases the competitive pressure on the organization, so reducing its performance. Their technological status argument builds upon the notion that, under conditions of uncertainty, resource controllers cannot readily observe the organization's actual quality, and therefore rely on their perception of the organization's quality, which is dependent upon the organization's relative reputation (i.e., status). Because technological development is characterized by high levels of uncertainty, status has an important role in directing resources in technological development. And the more resources available to the organization, the higher are its chances of survival.

Even though Podolny, Stuart, and Hannan (1996) build upon general ecological and economic insights to construct their eloquent arguments, some of their assumptions

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[15] Even though ecologists recognize that the density-dependence argument of organization ecology clearly allows for legitimative effects of crowding in the formative years of a population (Hannan, Pólos, & Carroll, 2007; Boone, Wezel, & van Witteloostuijn, 2007), most ecological studies equate niche overlap with competition (McPherson, 1983; Baum, 1994; Podolny & Stuart, 1995; Podolny, Stuart, & Hannan, 1996; Hannan, Carroll, & Pólos, 2003).

remain hidden because natural language is ambiguous. As a result, it is not precisely clear which conditions have to hold for their arguments to be valid or true. Accordingly, before we can integrate our insights into these arguments, we first need to explicate the underlying assumptions, resolve all ambiguity, and correct any possible flaw that might exist in their argumentation. To do so, we will use a process of logical formalization, which essentially implies that we translate their arguments into formal theory fragments. In doing so, we find that Podolny, Stuart, and Hannan (1996) equate technological crowding with competition only because they draw a sample of homogenous organizations from a highly competitive market. When relaxing this assumption, we accommodate the crowding argument for the existence of positive spillovers as well, hereby demonstrating that crowding cannot be universally equated with competition. Furthermore, in formalizing the technological status argument, we add technological quality as a dimension to the technological niche. Moreover, we demonstrate how the level of uncertainty surrounding the organization's technology mediates the relation between, on the one hand, the organization's technological status and quality, and, on the other hand, organizational performance.

The contribution of this chapter is threefold. First, we formalize the theory of the technological niche. By explicating its underlying assumptions, we make the theory more transparent, facilitating easy extension and cumulative development. Second, we extend the theory of the technological niche by distinguishing between technological space and market space (i.e., we distinguish between competitor versus non-competitor technological crowding). Furthermore, we add technological quality as a dimension to the technological niche, and demonstrate how uncertainty mediates the relationship between the organization's technological status, its actual quality, and its perceived quality. Third and finally, we offer yet another demonstration of how logic can be used in theory analysis and development.

The structure of this chapter is as follows. The next section will provide an overview of the process of logical formalization. Section 5.3 will discuss the language that we will use for our logical formalization. Based on these steppingstones, we will formalize the theory of technological niche in Section 5.4, and provide more insight into the theory's implicit assumptions. Finally, Section 5.5 concludes this chapter by placing our findings in the broader academic debate, and by suggesting several directions for future research.

5.2 Logical formalization

Within social sciences, most theory is stated in natural language. Events and entities in the real world are abstracted into labels and concepts, and are related to one another into a – preferably coherent and consistent – theory fragment or story. To facilitate the ease of communication, natural language does not require an explicit definition of each and every label and concept used in this process. After all, explicitly defining all labels and concepts at the outset of each and every communication would make it an extremely strenuous process, severely reducing the flow of communication by increasing its costs. In the context of theory building, the use of natural language initially facilitates theory development. After all, the boundaries of a theory can be easily explored by applying the theory's concepts and constructs to different contexts and at different levels of analysis. However, this extension of theory beyond its original domain can obscure the meaning of the theory's core concepts and constructs. That is, because there is no requirement to explicitly define and relate all concepts and constructs to one another, concepts and constructs can take on a completely different meanings in different contexts. For example, consider the following two sentences (adapted from Gamut, 1991a): (1) "Innovation is the successful introduction of an invention in the marketplace", and (2) "Innovation has ten letters". In sentence (1), the expression 'innovation' refers to the process of converting inventions into successful products and processes in a market; in sentence (2), the exact same expression refers to a word.

Obviously, when concepts take on different meanings in different contexts, contradictions and anomalies arise, which stifles the theory's further development. Thus, to facilitate theory development in this stage, it is necessary to formally define and relate all concepts and constructs at all levels of analysis to elucidate the precise composition of the theory's arguments. In doing so, contradictions can be resolved, and anomalies disappear. At this juncture, logical formalization is a extremely valuable tool as it enables us to systematically analyze the logical structure of an argument, and to "lay bare each argumentative step, thereby revealing potential loopholes (i.e., implicit assumptions), invalid references, and inconsistencies" (Bruggeman & Vermeulen, 2002: 185). A logical formalization essentially translates theoretical arguments (in natural language) into a formal theory. Formal theory is a set of sentences in a given formal language with an inference system. Subsequently, the set of sentences is closed under logical deduction and conclusions are validly inferred from premises according to the rules of inference (Bruggeman & Vermeulen, 2002). Hence, through a process of logical formalization, it is possible to eliminate anomalies by resolving contradictions, to end up with valid (i.e., if the premises are true, the conclusion logically follows from to the rules of inference) and explicit (i.e., all concepts are explicitly defined at the appropriate level of analysis) argumentative structures that provide the transparency needed for cumulative theory development.

To conduct our logical formalization, we use the methodology outlined by Bruggeman and Vermeulen (2002), which entails five steps: (1) marking the core theory, (2) analyzing key concepts, (3) informal axiomatization, (4) formalization proper, and, finally, (5) formal testing. Next, we will explain these steps in a highly condensed manner. First, marking the core theory implies identifying the major claims and their supporting arguments. To do so, Fisher (1988) has developed a useful methodology that basically entails scanning the text for conclusion, reason, and supposition indicators. A brief summary of this methodology is provided in Appendix C.

Second, the arguments have to be analyzed to find out what the core concepts (i.e., objects) and their properties are, and how they relate to one another. This is basically the hardest part of any formalization, sounding much easier than it actually is. For this, you need to interpret the work and place it in the right context. When doing so, it is important to consider that logical formalization is not a neutral approach to theory, and that different formalizations stand for different interpretations (Péli, 2007). Most work originates from a certain paradigm (or theoretical perspective) with many implicit assumptions, which may not be contained in the original text. Therefore, in analyzing the core theory, it is extremely important to get thoroughly acquainted with the theory, and to also rely on related work by the author(s) and to relate to the broader theoretical domain from which the work originates. Ask (yourself) what the author could have intended with the particular argument. After all, natural language is highly ambiguous, and it is all too easy to criticize other people's work.

Third, the goal of informal axiomatization is to represent the core theory as a set of relatively simple sentences, with a clear logical structure. This means that complex sentences should be broken up into simple sentences, and that the structure of each individual part should be clarified by connecting the events by using the logical connectives or constants in Table 5.1. At this point, any logical ambiguity needs to be resolved, and premises need to be added to the theory to make it logically sound and complete. To display the logical structure of the theory, it is extremely useful to use a diagram or model (Bruggeman & Vermeulen, 2002; Fisher, 1988).

Fourth, the formalization step entails the translation of the informal axiomatization into a formal language. A logical formalization can be done in many flavors or logical languages, and which language to use clearly depends on the issue at hand. A useful rule of thumb is to use the simplest language that can be used to complete the specific task (Bruggeman & Vermeulen, 2002). The simplest formal language is propositional logic, which is concerned with argumentative structures that only use the logical constants from Table 5.1 – anything else that affects the validity of arguments is left out (Gamut, 1991a). Next, first-order or predicate logic (FOL), accommodates the possibility of quantifying expressions (like 'all' and 'some') by adding the logical quantifiers (see Table 5.1), and is thus an extension of propositional logic. Notwithstanding the apparent simplicity of FOL, it provides for a rigorous and formal method to evaluate theory (Péli & Masuch, 1997), and has proven itself extremely valuable in many cases (Bruggeman & Vermeulen, 2002; Péli, 1997; Péli, Bruggeman, Masuch, & Nuallain, 1994).

Fifth and finally, regarding formal testing, for first-order logic software can be used to evaluate the soundness and consistency, and avoid human error. However, proving by hand helps to achieve a higher level of understanding of the theory and its logical structure, and logical problems can be discovered and repaired (Bruggeman & Vermeulen, 2002). This is also referred to as the process of "improving by proving" (Lakatos, 1976: 37). This concludes our process description of the formalization process. For a more in-depth description and application, we refer to Bruggeman and Vermeulen (2002), and Vermeulen and Bruggeman (2001).

5.3 Non-monotonic logic

We have already mentioned that first-order logic (FOL) is sufficient in most cases. However, unfortunately, FOL does not allow for exceptions. This implies that any contradiction results in a rejection of the whole theory, which makes it less suited for theory development. Therefore, in an attempt to develop a general foundation for organizational ecology, Hannan, Pólos, and Carroll (2007) use non-monotonic logic (NML), as this allows for empirical generalizations and exceptions. NML is therefore much better suited for theory building (Péli, 1997). In NML, when exceptions do occur that result in potential contradictions, the so-called specificity rule applies. This rule states that, when contradicting arguments exist, the more specific argument applies.

The penguin example illustrates this point rather eloquently. Consider the following three statements: (1) birds can fly, (2) penguins are birds, and (3) penguins cannot fly. Viewed individually, these statements are all considered true. However, when these statements are considered jointly, it results in an obvious contradiction. After all, according to these statements, can penguins fly or not? This 'problem' cannot be easily resolved using FOL, as the resulting contradiction leads to a rejection of the whole theory.[16] In NML, however, the specificity rule provides a rather simple way out of this contradiction.

To come back to our example, to determine whether penguins can fly, there are two alternative arguments that result in a contradicting conclusion. The latter argument is given directly by statement 3, which argues that penguins cannot fly. The former argument is provided by combining statements 1 and 2 (i.e., penguin is a bird, and a bird can fly, so it logically follows that a penguin can fly). Because the former argument needs two statements to reach its conclusion, while the latter only needs one, the latter and

[16] Even though it is possible to model this argument in FOL, this would entail altering the individual statement to prevent contradictions from arising in the first place. For example, in FOL, the first statement could be transformed so that all birds, except penguins, can fly. Obviously, taking into account all exceptions explicitly in general arguments makes the process of logical formalization rather cumbersome, especially for theory fragments that are currently being developed, and therefore subject to large amounts of change.

more specific argument applies. Essentially, it provides an exception to the alternative more general argument. It does so by using a set of alternative non-monotonic logical quantifiers (see Table 5.1). The argument then becomes as follows. Normally, (1) birds can fly; however, (2) a penguin is a specific kind of bird; and (3) a penguin cannot fly.
In NML, if there is no clear specificity ordering between contradicting arguments (i.e., if the contradicting arguments are of the same length), the theory refrains from drawing any conclusions. This means that contradicting perspectives are allowed to co-exist side by side until more evidence resolves the contradiction, which more closely resembles the process of actual theory development. After all, theories are not rejected upon occurrence of a single anomalous or contradictory finding (Kuhn, 1996). Another difference between FOL and NML are the argumentation patterns (i.e., valid argumentative structures) that are part of the inference systems. More specifically, NML drops two argumentation patterns from its inference system, as these imply unwanted conditions for theory building (Hannan et al., 2007), see Appendix D. As it is our aim to further develop the technological niche within the general ecological framework of Hannan, Pólos, and Carroll (2007), we also opt for the non-monotonic logical flavor. For a more in-depth discussion of non-monotonic logic, we refer to Hannan, Pólos, and Carroll (2007); and for a good elementary textbook on logic in general, see Gamut (1991a; 1991b).

Even though logical formalization is not a neutral approach to theory, and different formalizations stand for different interpretations (Péli, 2007), it opens the door for debate and for the resolution of inconsistencies, and thus facilitates the development of a sound and consistent theory (fragment). Hence, logical formalization enables the reconciliation of seemingly contradictory theory fragments, and to integrate middle range theories into more universal ones (Merton, 1968b). Some recent examples within the domain of organizational ecology are the integration of pre-entry ecologies and density-delay theory by Kuilman, Vermeulen, and Li (2007), of Red Queen evolution and inertia theory by Peli (2007), and of different age dependence theory fragments by Hannan (1998) and Hannan, Pólos, and Carroll (2007).

According to Weick (1979), any good scientific theory of organization must balance the scientific objectives of generality, simplicity, and accuracy. This balancing act implies that it is always a matter of choice what to include explicitly (i.e., in the foreground) in a logical formalization and what not (i.e., in the background). In other words, we need to select these elements in our analysis that make our arguments as general, simple, and accurate as possible. Here, we employ the four background assumptions that are listed in Appendix E. Table 5.1 summarizes the logical constants, quantifiers, set operators, predicates and functions used in our analysis. Now that we have explained our formal apparatus, we proceed with our logical formalization of the technological niche. We should note that we only report the outcome of our formalization of Podolny, Stuart, and Hannan (1996; henceforth referred to as PSH), and do not describe the formalization process in detail.

Table 5.1 Glossary of symbols

Logical constants		
	$\wedge$	conjunction (e.g., A and B)
	$\vee$	disjunction (e.g., A and/or B)
	$\rightarrow$	material implication (e.g., if A, then B)
	$\longleftrightarrow$	material equivalence (e.g., A if and only if B)
	$\neg$	Negation (e.g., not A)
Logical quantifiers		
	$\exists$	classical existential quantifier (e.g., A exists)
	$\forall$	classical universal quantifier (e.g., for all A)
Non-monotonic logical quantifiers		
	$\mathfrak{N}$	non-monotonic 'normally' quantifier (e.g., normally A)
	$\mathfrak{A}$	non-monotonic 'ad-hoc' quantifier (e.g., assumably A)
	$\mathfrak{P}$	non-monotonic 'presumably' quantifier (e.g., presumably A)
Set operators		
	$\cap$	intersection of two sets (i.e., common elements in both sets)
	$\cup$	union of two sets (i.e., all elements from both sets)
	$\lvert\cdot\rvert$	cardinality of a set (i.e., the number of unique elements in the set)
	$\setminus$	set subtraction (i.e., subtract elements of one set from another set)
Predicates		
	$O(x)$	x is an organization
	$C(x,y)$	organization y actively competes with organization x
Functions		
	$CO(x,y)$	overlap of organization x's technological competencies with organization y
	$CP(x)$	total competitive pressure experienced with organization x
	$LP(x)$	total legitimative pressure experienced with organization x
	$N(x)$	the novelty of organization x's technology
	$NO(x,y)$	overlap of organization x's technological niche by organization y
	$P(x)$	organization x's performance
	$PQ(x)$	perceived technological quality of organization x
	$Q(x)$	technological quality of organization x
	$S(x)$	technological status of organization x
	$TA(x,y)$	overlap of organization x's technological antecedents by organization y
	$UC(x)$	uncertainty surrounding the technology of organization x

5.4 Formalizing the theory of the technological niche

In the previous chapter, we applied the technological niche at the level of technology, in an effort to illuminate aggregated patterns of technological development. This generated insights (i.e., the existence of different technological domains characterized by different stages of development) that are also important for individual organizations. However, before we can effectively transfer these insights to the organizational level of analysis, we need to make the current theoretical arguments logically consistent, sound, and complete. This also makes the arguments explicit and transparent, and thus enables an easy integration of the insights from the previous chapters.

The organization-specific technological niche was first conceived by PSH, so we build upon their work to formalize our arguments. In their study, PSH do not provide a clear and strict separation between the dyadic and the organizational level of analysis. However, logically formalizing their arguments requires us to explicitly define the level of analysis at which to put forward our arguments. PSH's main claims are formulated at the organizational level of analysis, making the case for formulating our arguments at this level as well. However, we choose to formulate our arguments mainly at the dyad level of analysis, as this facilitates the theoretical extensions we have envisioned in the next chapter. We can now continue with the actual formalization.

5.4.1 Technological crowding

PSH's technological crowding argument builds upon the general crowding argument in organizational ecology, which states that the intensity of competition among organizations in a population is largely a function of the similarity in resource requirements. More specifically, the more similar the resource requirements, the greater the potential for competition (Baum & Singh, 1994b; Hannan & Freeman, 1977). The similarity in resource requirement is commonly referred to as niche overlap, and in the context of technological development, the "niche overlap between two organizations […] can be regarded as a function of the degree of common dependence on prior inventions as foundations for their research activity" (Podolny et al., 1996: 665). After all, these prior inventions or technological antecedents are the organization's constituents of innovation. Hence, the organization's technological antecedents are the resources in the organization's recombination process to generate novel technological recombinations or inventions. So, the more that two organizations share the same technological antecedents, the more similar are their resource requirements and, hence, the greater their technological niche overlap. Let $O(x)$ be the predicate that indicates that x is an organization, and let $TA(x,y)$ be the function that specifies the extent to which organization x shares technological antecedents with organization y. We can now define

$TA(x,y)$ as follows (for brevity, we will frequently refer to a focal organization as 'focal' only, and to an alter organization as 'alter' only).

Definition 5.1

The extent to which focal shares technological antecedents with alter is equal to the cardinality of the intersection of the sets of technological antecedents of both organizations, divided by the cardinality of the technological antecedents of focal.

$$TA(x, y) = \frac{|A_x \cap A_y|}{|A_x|}$$

where A_x refers to the antecedents of the inventions of organization x, and A_y to the antecedents of the inventions of organization y, and $|.|$ to the cardinality of a set (i.e., the number of unique elements contained within the set). Note that x and y can refer to the same organization at different times or to different organizations at the same time.[17]

As can be deduced from the formula above, the overlap in technological antecedents is asymmetric. This implies that the overlap of the technological antecedents of organization x with organization y is not necessarily equal to the overlap of the technological antecedents of organization y with organization x. Now, let $NO(x,y)$ be a function that specifies the overlap of organization x's technological niche with organization y. We now have all our ingredients to formulate our first postulate.

Postulate 5.1

The more that focal shares technological antecedents with alter, the greater the overlap of focal's technological niche by alter.

$\mathfrak{N}\, x,x',y,y'\ [TA(x,y) > TA(x',y') \rightarrow NO(x,y) > NO(x',y')]$

On page 66, PSH subsequently argue that "a like pattern of technological antecedents implies a similarity – or even redundancy – in technological competencies." Strictly following their argument would thus require us to formally relate the organizations' shared technological antecedents to an overlap in technological competencies. However, we choose not to do so, and thus to deviate from their original argument. Instead, we argue that the organizations' niche overlap actually leads to an overlap in their technological competencies. There are two reasons for our alternative logic. First of all, this makes the argument logically sound. Otherwise, it would be

[17] In the current chapter, we do not explicitly take into account time in our logical formalization for two reasons. First of all, it is not required to formalize the arguments of PSH. Second, excluding time makes the formalization easier to understand for laymen. However, in our next chapter, we step it up a notch, and do include time in our formalization.

impossible to directly relate niche overlap to an overlap in technological competencies in a formal way. As can be seen in Figure 5.1, according to the original argument, both niche overlap and competencies overlap are a function of shared technological antecedents. This implies that increasing niche overlap in the original argument does not necessarily lead to an increase in competencies overlap. Naturally, this also has severe consequences for the relation of niche overlap to organizational performance, as indicated by the suggested theorem.[18]

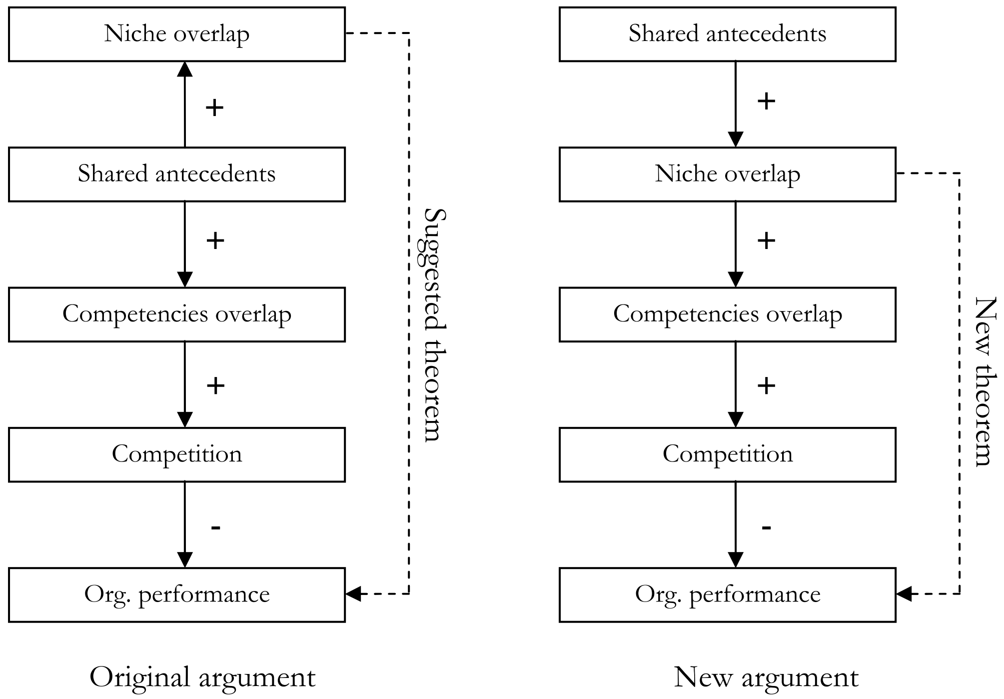

Figure 5.1 Original and new argumentative structure of the crowding theorem

In contrast, according to the new argument, the overlap in technological competencies is a function of niche overlap, and not of shared technological antecedents.[19] This means that increasing niche overlap does increase the overlap in technological competencies, implying that the theorem between niche overlap and organizational performance is not conditional on the origin of the increase in niche overlap. This naturally brings us to our second motive for deviating from the original argument. We want to provide a foundation for a general framework that, amongst

[18] In the original argument, the suggested theorem would be as follows: increasing niche overlap through increasing shared technological antecedents increases organizational mortality.

[19] An alternative solution would be to relate shared technological antecedent and niche overlap to one another using material equivalence (see Table 5.1) – i.e., to equate an overlap in technological antecedent with niche overlap. Even though this would also make the theorem logically sound, this would not allow niche overlap to result from anything else than sharing technological antecedents.

others, relates (technological) niche overlap to organizational performance. Because niches are multidimensional, we need to allow for the possibility that niche overlap between two organizations results from more than just an overlap in technological antecedents. After all, niche overlap can also increase due to other reasons than an increase in shared technological antecedents.

For example, consider the distinction between two organizations that develop highly similar technology (e.g., recombinant DNA and monoclonal antibodies) versus highly distinct technology (e.g., biotech and automotive). It goes without saying that the organizations with technologies that are more intimately linked have a greater niche overlap than the organizations with unrelated technologies. So, by accommodating for the possibility that niche overlap increases due to other reasons than an increase in shared technological antecedents, we open the door for future work into the multidimensionality of (technological) niche overlap. Furthermore, different research questions require emphasizing different (combinations of) dimensions, and thus different measures of niche overlap. Let $CO(x,y)$ be the function that specifies the overlap or organization *x*'s technological competencies by organization *y*, we then have all the necessary elements for our next assumption

Postulate 5.2

The greater (equal) the overlap of focal's technological niche by alter, the greater (equal) the overlap of focal's technological competencies by alter.

$\mathfrak{N}\ x,x',y,y'\ [NO(x,y) > NO(x',y') \rightarrow CO(x,y) > CO(x',y') \wedge (NO(x,y) = NO(x',y') \rightarrow \mathrm{CO}(x,y) = \mathrm{CO}(x',y'))]$

As previously noted, in analogy to standard organizational ecology logic, PSH argue that an overlap in technological competencies leads to competition. However, they studied the effects of crowding and status among 113 merchant and major captive producers in the semiconductor industry, with more than $10 million in sales. In doing so, the authors make the implicit assumption of homogenous actors operating in a single, crowded market. As a consequence, all actors use their technological competencies to actively compete in this crowded market. Therefore, the fact that they are able to equate technological niche overlap with competition is merely a reflection of drawing a sample from a competitive market (Pontikes, 2007), and is not an appropriate representation of the complete theoretical space. As we will demonstrate in this chapter, an alternative research design would lead to different conclusions.

We thus need to add the limitation that for niche overlap to result in competition, the actors have to be active in a competitive market – or, in other words, they have to be competitors. We therefore introduce the predicate $C(x,y)$ that specifies that two organizations are actively competing. Now we can formally relate an overlap in technological competencies to an increase in the competitive pressure experienced by the focal organization. Let $CP(x)$ be the competitive pressure experienced by organization x. Our last predicate specifies the competitive pressure at the organizational level of analysis, while the overlap in technological competencies is specified at the dyad level of analysis. This means that to formally relate these to one another, we need to aggregate the dyad level to the organizational level.

However, before we can do so, we first need introducing two dyadic coefficients, to delineate the legitimation and competition effect of one organization on another. By defining two coefficients, we allow the competition and legitimation effects to differ. Moreover, these coefficients allow organizations to partially compete and/or legitimate one another. After all, organizations can compete in some but not all markets, hereby altering the competitive pressure that one exerts on the other. Other processes can also alter the competitive intensity between two organizations, such as multimarket competition (Barnett, 1991; Witteloostuijn, 1990), strategic alliances (Doz & Hamel, 1998), and (market) resource partitioning (Carroll & Hannan, 2000). Without doubt, the legitimative strength alters between sets of organizations as well.

Postulate 5.3

Focal does not compete with itself and if focal and alter are actively competing, their competition coefficient is greater than their legitimation coefficient, and when they are not actively competing, their competition coefficient is smaller than their legitimation coefficient.

$\mathfrak{P}\, x,y\ [\neg C(x,x) \wedge C(x,y) \rightarrow \gamma_{xy} > \lambda_{xy} \wedge \neg C(x,y) \rightarrow \gamma_{xy} < \lambda_{xy}]$

Next, we need to define an auxiliary assumption to set the competitive and legitimative effect between pairs of organizations equal to one another. This allows us to easily compare pairs of organizations without the need to consider the implications of different competitive and legitimative effects between pairs of organizations. In the next chapter, we will relax this assumption and do consider the implications.

Auxiliary assumption 5.1

The competitive and legitimative pressure between pairs of (non-) competing organizations is equal.

$\mathfrak{A}\, x,x',y,y'\ [(\neg C(x,y) \wedge \neg C(x',y')) \vee (C(x,y) \wedge C(x',y')) \rightarrow (\gamma_{xy} - \lambda_{xy}) = (\gamma_{x'y'} - \lambda_{x'y'})]$

Definition 5.2

The total competitive pressure at the organizational level is equal to the sum of the organization's dyadic competitive pressures which is equal to the dyadic competition multiplier times the dyadic competencies overlap.

$$CP(x) = \sum_{y}^{Y} CP(x,y) = \sum_{y}^{Y} \gamma_{xy} \cdot CO(x,y)$$

where y refers to an individual element of the set of all organizations Y.[20]

Hence, an overlap in technological competencies only results in competition if both organizations are competitors (i.e., if $C(x,y)$ is true or $\gamma_{xy} = 1$). The question that remains is what happens if this limiting assumption is relaxed – that is, what happens if focal and alter are not actively competing with one another (i.e., if $C(x,y)$ is false or $\gamma_{xy} = 0$)? Allowing for the possibility that the organizations are not actively competing implies a distinction between crowding in technological space and crowding in market space. This was already recognized by Pontikes (2007). By distinguishing between competitor and non-competitor technological (knowledge) crowding she demonstrates that, due to the existence of knowledge spillovers, technological crowding by non-competitors has a positive effect on the organizations performance.

However, not only knowledge spillovers generate a positive effect of niche crowding. After all, according to density dependence theory, in the formative stage of a market, crowding has a positive influence due a process of legitimation as well (Hannan et al., 2007).[21] Moreover, crowding is argued to enhance the development and accumulation of common knowledge (Fleming & Sorenson, 2004; Jaffe, 1986; Levin, 1988), to enable a sharing of infrastructure and the creation of economies of standardization (Baum & Haveman, 1997; Wade, 1995), and to facilitate vicarious learning (Delacroix & Rao, 1994). This means that we clearly need to accommodate for a positive effect of crowding as well. Let $LP(x)$ be the total legitimative force experienced by organization x. Again, our last predicate specifies the legitimative force at the organizational level of analysis, while the overlap in technological competencies is specified at the dyad level of analysis. This means that to formally relate these to one another, we again need to aggregate the dyad level to the organizational level. We do so by the following definition.

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[20] By applying the summation in Definition 5.2, we implicitly move from a first order to a second order logical formalization.

[21] Even though the concept of legitimation is mainly used in the context of density dependent legitimation of organizational forms, we believe that it can also be effectively used at the level of individual organizations.

Definition 5.3

The total legitimative force at the organizational level is equal to the sum of the organization's dyadic legitimative pressures which is equal to the dyadic legitimation multiplier times the dyadic competencies overlap.

$$LP(x) = \sum_{y}^{Y} LP(x, y) = \sum_{y}^{Y} \lambda_{xy} \cdot CO(x, y)$$

where y refers to an individual element of the set of all organizations Y.

Even though PSH focus on the organization's life chances in their hypotheses, the hypotheses are actually tested using sales growth data. They subsequently argue that "the arguments about the effects of status and crowding on life chances potentially apply to a range of measurable outcomes: mortality rates, growth rates, profitability, success in attracting employees or external partners, and so forth" (1996: 671). Hence, we also opt for a general construct (i.e., organizational performance) in our logical formalization, which includes multiple outcomes that can be more (e.g., organizational mortality) or less (e.g., organization innovation) distant in time.

So, now that we have defined the competitive and legitimative forces at the organizational level, we can relate this to the organization's performance. Following standard economic logic, and under the ceteris paribus assumption, the more competition is experienced by the organization, the lower its performance; similarly, the more legitimation is experienced by the organization, the higher its level of performance (Hannan & Freeman, 1989). Let $P(x)$ be the predicate that specifies organization x's performance. This leads us to our following postulates.

Postulate 5.4

If the legitimation experienced by focal is not greater than the legitimation experienced by alter, and the competition experienced by focal is greater than the competition experienced by alter, then the performance of focal is lower than the performance of alter.

$\mathfrak{N}\, x,x'\ [LP(x) \leq LP(x') \wedge CP(x) > CP(x') \rightarrow P(x) < P(x')]$

Postulate 5.5

If the competition experienced by focal is not greater than the competition experienced by alter, and the legitimation experienced by focal is greater than the legitimation experienced by alter, then the performance of focal is greater than the performance of organization alter.

$\mathfrak{N}\, x,x'\ [CP(x) \leq CP(x') \wedge LP(x) > LP(x') \rightarrow P(x) > P(x')]$

Now, we have all the necessary elements to prove our theorems (i.e., to formally relate niche overlap to the organization's performance).

Theorem 5.1

If focal and alter are competitors, the greater the overlap of the focal organization's technological niche by alter, the lower the focal organization's performance.

$$\mathfrak{P}\, x,x',y,y'\ [C(x,y) \wedge C(x',y') \wedge NO(x,y) > NO(x',y') \ \wedge \forall z,z'\ [y \neq z \wedge y' \neq z' \wedge \sum_{z} CP(x,z) \geq \sum_{z'} CP(x',z') \wedge \sum_{w} LP(x,z) \leq \sum_{w'} LP(x',z')] \rightarrow P(x) < P(x')]$$

Proof for this theorem is provided by auxiliary assumption 5.1, postulates 5.2, and 5.5, and definition 5.2 and 5.3 (see Appendix F).

Theorem 5.2

If focal and alter are not competitors, then greater the overlap of the focal organization's technological niche by alter, the higher the focal organization's performance.

$$\mathfrak{P}\, x,x',y,y'\ [\neg C(x,y) \wedge \neg C(x',y') \wedge NO(x,y) > NO(x',y') \ \wedge \forall z,z'\ [y \neq z \wedge y' \neq z' \wedge \sum_{z} CP(x,z) \leq \sum_{z'} CP(x',z') \wedge \sum_{w} LP(x,z) \geq \sum_{w'} LP(x',z')] \rightarrow P(x) < P(x')]$$

Proof for this theorem is provided by auxiliary assumption 5.1, postulates 5.2, and 5.5, and definition 5.2 and 5.3 (see Appendix F).

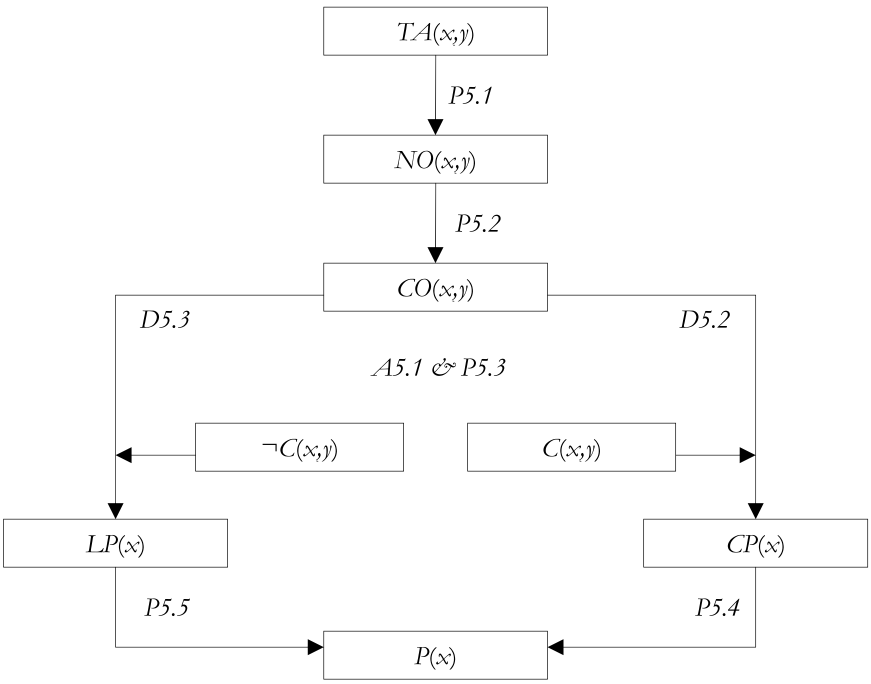

Figure 5.2 Structure of technological crowing argument

We have already mentioned that a diagram or model is useful to display the structure of our argument. We therefore include this diagram in Figure 5.2. In this picture, *P* refers to postulates, *D* to definitions, and *A* to auxiliary assumptions. This concludes the formalization of the crowding theorem. We now continue with formalizing our second technological niche dimension – technological status.

5.4.2 Technological status

Technological development is characterized by pervasive uncertainty (Rosenberg, 1996), even for basic and well-established technologies (Podolny & Stuart, 1995). In this uncertain environment, resource controllers or stakeholders (e.g., investors, employees, customers, and government officials) must decide where to invest their resources. However, due to the inherent uncertainty, an organization's technical properties or technological characteristics fail as a reliable guide (Anderson & Tushman, 1990; Podolny & Stuart, 1995). To cope with the uncertainty surrounding the organization's technological quality, resource controllers have to resort to other information on which to base their resource allocations. Therefore, resource controllers rely on the organizations' reputations to determine where to invest their scarce resources. More specifically, they consider an organization's reputation relative to the reputation of all other organizations in the population, also referred to as an organization's status.

Status thus represents the position of an organization – or any other actor, for that matter – in the social structure or hierarchy. As such, it is an instance of endogenous population structuring that results from the dynamics of the interactions of organizations in the population (Podolny et al., 1996). To be precise, status arises from acts of deference from other organizations (Podolny, 1993). In the context of technological development, status refers to the organization's perceived technological quality, and is a function of the importance of the organization's previous contributions to the advancement of technology (Podolny et al., 1996). Accordingly, as other organizations build upon the focal organization's technology, a certain legitimacy or status is conferred on the focal organization's technology. Now, let $S(x)$ be the predicate that refers to the status of organization x. We can now define status as follows.

Definition 5.4

The technological status of an organization is the organization's share of the total acts of deference of all organizations in the population.

$$S(x) = \frac{D_x}{\sum_y^Y D_y}$$

where D_x refers to the acts of deference that organization x receives, D_y refers to acts of deference that organization y receives, and Y refers to all organizations in the population.

Again, we do not strictly follow the line of thought of Podolny, Stuart, and Hannan (1996). Undeniably, we do recognize the importance of status in contributing to the perceived quality of the organization's technology. However, instead of equating status with the perceived quality of the organization's technology, we argue that an organization's perceived quality is influenced not only by the organization's status (i.e., the contribution of the organization to past technological developments), but also by the actual quality of the organization's technology. Let $Q(x)$ be the function that specifies the organization's actual technological quality, which we define as follows.

Definition 5.5

The technological quality of an organization is the organization's share of the total technology of all organizations in the population.

$$Q(x) = \frac{T_x}{\sum_{y}^{Y} T_y}$$

where T_x refers to the share of technology that is owned by organization x, T_y refers to the share of technology that is owned by organization y receives, and Y refers to all organizations in the population.

Consequently, instead of assuming that the actual quality of the organization's technology is completely obscured, we argue that the extent to which the organization's technological quality is masked is determined by the level of uncertainty surrounding its technology. After all, in a relatively certain environment, where technological standards are well known and change is of a highly incremental and cumulative nature, the quality of an organization's technology can be readily observed by resource controllers in the environment. That is, only when members of the technological community are unable to perceive the actual quality of the organization's technology do they need to rely on the organization's past quality or status. Hence, the perceived quality of the organization's technology is dependent on both its status and its actual technological quality, and this relationship is mediated by the level of uncertainty surrounding an organization's technology. Before we can continue and define precisely how uncertainty mediates this relationship, we need to define uncertainty.

Let us assume that $UC(x)$ is the level of uncertainty surrounding organization x's technology, and let us furthermore assume that the level of uncertainty can be represented by an interval that ranges between 0 (complete certainty) to 1 (complete uncertainty). For simplicity, we do not assume that uncertainty reaches its extreme values of 0 or 1.

Postulate 5.6

The uncertainty function of an organization's technology maps organizations to the ⟨0,1⟩ interval.

$\mathfrak{N}\, x\, [0 < UC(x) < 1]$

We can now define how the relationship between the organization's perceived quality and its status and actual quality is mediated by the level of uncertainty. Let $PQ(x)$ be the perceived quality of organization x's technology, let $S(x)$ be organization x's status, and let $Q(x)$ be the actual quality of organization x's technology. We can now add the following definition to our knowledge base.

Definition 5.6

The perceived quality of the organization is defined as the sum of the effect of status and quality.

$PQ(x) = (1 - UC(x)) \cdot Q(x) + UC(x) \cdot S(x)$

As can be deduced from definition 5.6, the extent to which a change in uncertainty actually increases or decreases the perceived quality of the organization depends on both the level of the organization's technological status and quality. On the one hand, if the organization's status is higher than its quality (recall that both status and quality are defined relative to all population members), decreasing uncertainty decreases the perceived quality of the organization. On the other hand, if the quality is higher than its status, decreasing uncertainty increases the organization's perceived quality. Now, we continue and relate the organization's perceived quality to its ability to mobilize resources.

As mentioned above, resource controllers or stakeholders use the perceived technological quality to guide their decisions on where to invest their resources. This means that increasing the perceived technological quality of the organization relieves the organization's problem of mobilizing resources to build, to sustain, and to expand its operations (Podolny, 1993; Stinchcombe, 1965). That is, increasing the perceived quality of the organization's technology increases the organization's ability to mobilize resources, which in turn, according to standard economic logic, increases the organization's performance. Let $MR(x)$ be organization x's ability to mobilize resources. We can now add the following propositions to our theory.

Postulate 5.7

If the perceived quality of focal is larger than the perceived quality of alter, the focal's ability to mobilize resources is greater than the ability of alter to mobilize resources.

$\mathfrak{N}\, x,x'\, [PQ(x) > PQ(x') \rightarrow MR(x) > MR(x')]$

Postulate 5.8

If the ability of focal to mobilize resources is larger than the ability of alter to mobilize resources, then focal's performance is greater than alter's performance.

$\mathfrak{N}\ x,x'\ [MR(x) > MR(x') \rightarrow P(x) > P(x')]$

Now we have everything in place to formally relate the organization's technological status and quality to its performance, which is done in the theorems below.

Theorem 5.3

If (a) the uncertainty surrounding focal's technology is equal to the uncertainty surrounding alter's technology, (b) the quality of focal's technology is not smaller than the technological quality of alter, and (c) the status of focal is greater than the status of alter, then the performance of focal is greater than the performance of alter.

$\mathfrak{P}\ x,x'\ [UC(x) = UC(x') \wedge Q(x) \geq Q(x') \wedge S(x) > S(x') \rightarrow P(x) > P(x')]$

Proof for this theorem is provided by definition 5.6, and postulates 5.7 and 5.8 (see Appendix F).

Theorem 5.4

If (a) the uncertainty surrounding focal's technology is equal to the uncertainty surrounding alter's technology, (b) the status of focal is not smaller than the status of alter, and (c) the quality of focal's technology is greater than the technological quality of alter, then the performance of focal is greater than the performance of alter.

$\mathfrak{P}\ x,x'\ [UC(x) = UC(x') \wedge Q(x) > Q(x') \vee S(x) \geq S(x') \rightarrow P(x) > P(x')]$

Proof for this theorem is provided by definition 5.6, and postulates 5.7 and 5.8 (see Appendix F).

Theorem 5.5

If (a) focal's status is higher than its quality, (b) focal's status is not smaller than the status of alter, (c) focal's quality is not smaller than the quality of alter, and (d) the uncertainty surrounding focal's technology is higher than the uncertainty surrounding the technology of alter, then the performance of focal is higher than the performance of alter.

$\mathfrak{P}\ x,x'\ [S(x) > Q(x) \wedge S(x) \geq S(x') \wedge Q(x) \geq Q(x') \wedge UC(x) > UC(x') \rightarrow P(x) > P(x')]$

Proof for this theorem is provided by definition 5.6, and postulates 5.6 to 5.8 (see Appendix F).

Theorem 5.6

If (a) focal's status is lower than its quality, (b) focal's status is not greater than the status of alter, (c) focal's quality is not greater than the quality of alter, and (d) the uncertainty surrounding focal's technology is higher than the uncertainty surrounding the technology of alter, then the performance of focal lower than the performance of alter.

$\mathfrak{P}\, x,x' \, [S(x) < Q(x) \wedge S(x) \leq S(x') \wedge Q(x) \leq Q(x') \wedge UC(x) > UC(x') \rightarrow P(x) < P(x')]$

Proof for this theorem is provided by definition 5.6, and postulates 5.6 to 5.8 (see Appendix F).

Theorems 5.5 and 5.6 imply that, on the one hand, high-status, low-quality organizations (i.e., low-quality incumbents) benefit most from uncertainty. On the other hand, high-quality, low-status organizations (i.e., high-quality new entrants) benefit most from certainty.

To determine the level of uncertainty surrounding the quality of the organization's technology, PSH use the level of crowding (i.e., niche overlap) of the organization's technological niche as a proxy. More specifically, they argue that an organization that has few potential competitors with similar technological antecedents has a more novel technology than an organization in a niche crowded with organizations with similar technological antecedents. Furthermore, they argue that the more novel an organization's technology, the more uncertain the quality of the technology. This means that PSH implicitly assume that uncertainty is an organizational characteristic only. However, we believe that this is merely an auxiliary assumption to complete their model. After all, in their discussion of status on page 667, PSH themselves argue that uncertainty is also property of a technological community or domain. We therefore represent this as an auxiliary assumption, and not as a substantive part of the theory. Let $N(x)$ be the novelty of the organization's technology. We can now formulate the following auxiliary assumptions.

Auxiliary assumption 5.2

If the overlap or focal's technological niche is greater than (equal to) the overlap of the technological niche of alter, then the novelty of focal's technology is smaller than (equal to) the novelty of the technology of alter.

$\mathfrak{A}\, x,x' \, [NO(x) > NO(x') \rightarrow N(x) < N(x') \wedge NO(x) = NO(x') \rightarrow N(x) = N(x')]$

Auxiliary assumption 5.3

If the novelty of focal is greater than (equal to) the novelty of alter, then the uncertainty surrounding focal's technology is greater than (equal to) the uncertainty surrounding the technology of alter.

$\mathfrak{A}\ x,x'\ [N(x) > N(x') \rightarrow UC(x) > UC(x') \wedge N(x) = N(x') \rightarrow UC(x) = UC(x')]$

Using these auxiliary assumptions, we can reformulate our theorems to make them consistent with the argumentative structure of PSH.

Theorem 5.7

If (a) the overlap of focal's technological niche is equal to the overlap of the technological niche of alter, (b) the quality of focal's technology is not smaller than the quality of alter, and (c) the status of focal is greater than the status of alter, then the performance of focal is greater than the performance of alter.

$\mathfrak{P}\ x,x'\ [NO(x) = NO(x') \wedge Q(x) \geq Q(x') \wedge ST(x) > ST(x') \rightarrow P(x) > P(x')]$

Proof for this theorem is provided by auxiliary assumptions 5.2 and 5.3, definition 5.6, and postulates 5.7 and 5.8 (see Appendix F).

Again, we provide a diagram of the argumentative structure of our status argument, now in Figure 5.3. In this diagram, the theorems are not so clearly distinguishable, as the intricate relationship between uncertainty, actual quality, status, and the perceived quality requires specifying all relationships in all theorems.

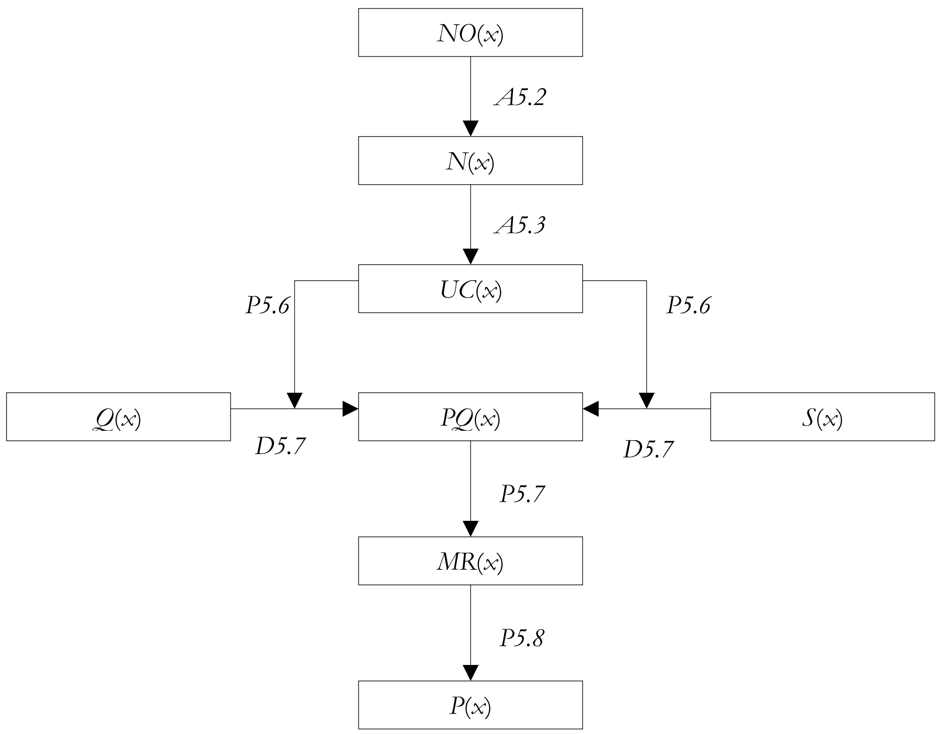

Figure 5.3 Structure of technological status argument

Only theorem 5.7 is distinct from the others because it also includes niche overlap (*NO*) and technological novelty (*N*), while theorems 5.3 to 5.6 do not. Again, *P* refers to postulates, *D* to definitions, and *A* to auxiliary assumptions. This concludes our logical formalization. Next, we will discuss our findings in greater detail, place them in the wider academic debate, and provide several avenues for future research.

5.5 Discussion and conclusion

The basis of our work is the organization-specific technological niche as conceived by PSH. By formalizing their arguments, we have explicated its underlying assumptions, supplemented assumptions where necessary, and corrected some minor inconsistencies in the argumentative structure. In all, we have developed two logically sound, consistent, and complete theoretical arguments (and provide the formal proof for their arguments in theorems 5.1 and 5.7, see Appendix F). In doing so, we have also extended the theory of the organization-specific technological niche. More specifically, by distinguishing competitor from non-competitor technological crowding, we demonstrate that the effect of technological crowding on organizational performance is conditional upon whether the organizations actually compete in the marketplace. In doing so, we essentially distinguish between crowding in technological space and crowding in market space (Pontikes, 2007).

In this chapter, we accommodate for the distinction between competitor and non-competitor technological crowding by introducing a competition and a legitimation coefficient, and posit that (not) actively competiting organizations have a higher (lower) competition coefficient than a legitimation coefficient. This allows plugging in – and thus an analysis of – characteristics that are known to impact the degree of competition and legitimation between organizations, such as, for example, multimarket competition (Barnett, 1991; Witteloostuijn, 1990), strategic alliances (Doz & Hamel, 1998), and (market) resource partitioning (Carroll & Hannan, 2000). An interesting question in this respect is what precisely determines the relationship between the competition and legitimation coefficient.

Moreover, a distinction between market and technology space also opens the door for further investigation into the interdependence between crowding in the different spaces or domains in which the organization is active. For example, a possible distinction would be between science, technology, and market space. Of course, more fine-grained distinctions are also possible (e.g., market space can be further subdivided into labor market space, capital market space, and product market space). In conjunction with the distinction between the real and fundamental niche (Hannan & Freeman, 1989), it is possible to connect these different domains or spaces. For example, the real niche in science space forms the basis for the fundamental niche in technological space, and the realized niche in technological space provides the basis for the fundamental niche in market space. Obviously, such a unidirectional relationship between science, technology, and market-space is rather simplistic, and more intricate relationships are closer to reality. However, in our view, this unidirectional relationship could provide a baseline that would allow a more process-oriented analysis (of the evolution) of organizations.

In addition, we have added relative technological quality as a dimension to the organization-specific technological niche. We demonstrate how the effect of technological quality and status on organizational performance is mediated by the level of uncertainty surrounding the organization's technology. In doing so, we demonstrate that, on the one hand, high-quality, low-status organizations should try to minimize the level of certainty, while, on the other hand, low-quality, high-status organizations should strive to maximize the uncertainty surrounding their technology (cf. Theorems 5.5 and 5.6) However, underlying this conclusion is the implicit assumption that the uncertainty surrounding the organization's technology is an organizational characteristic only, which affects all the organization's technologies in exactly the same way. We have already demonstrated in the previous chapter that this is an incorrect assumption. After all, uncertainty is to a large extent a property of a technological domain, and is influenced by the stage of development of that domain. Hence, relaxing the assumption that uncertainty is an organizational characteristic only also allows relaxing the implicit and incorrect assumption of a single and homogeneous technological domain.

As mentioned above, by explicating the assumptions, we make the theory of the organization-specific technological niche more transparent, hereby facilitating theory extension. We will demonstrate this in the next chapter, where we integrate some of our findings from the previous chapters in the theory of the organization-specific technological niche. More specifically, we will accommodate the theory for the existence of multiple technological domains in different stages of development. Another avenue that we have briefly touched upon in this chapter, which is worth exploring in greater detail, is the multidimensionality of the technological niche and, as a obvious consequence, the multidimensionality of niche overlap. Even though we have only used one dimension in determining niche overlap, our theory allows adding several other dimensions, such as: (i) the extent to which organizations actually develop the same technology (e.g., extent to which technologies are classified in the same categories or domains), (ii) the extent to which organizations build on each other's technology (e.g., by investigating cross-citation patterns), (iii) the extent to which organization combine the same technological components (cf. Fleming, 2001), and (iv) the extent to which organizations share the same technology alliance partners. The potential dimensions are plentiful, and which ones to focus on depends on the research question at hand (Hannan & Freeman, 1989).

Chapter 6

A Logical Extension of the Theory of the Technological Niche

6.1 Introduction

In Chapter 5, we have formalized the theory of the technological niche to make its argumentative structure more transparent, logically sound and complete. In doing so, we have revealed several of its underlying assumptions. By relaxing the assumption of homogenous actors operating in a single, highly competitive market, we have extended the theory beyond technological space to include market space. In addition, we have also introduced quality as a dimension of the technological niche. In the current chapter, our aim is to further extend our formal arguments, by integrating several of our major findings from Chapters 3 and 4. That is to say, we will assume that (1) organizations are embedded in a technological landscape that consists of multiple technological systems, (2) technological systems can be characterized by two stages of technological development (i.e., seed and growth), (3) technological systems provide distinct sets of opportunities, and, finally, (4) technological systems provide a distinct level of uncertainty.

As we will demonstrate in this chapter, these four assumptions not only have far-reaching consequences for our existing arguments, but also result in two additional arguments. First, when considering the lineage of technological development (cf. Figure 1.3), again, three dimensions of technological diversity can be conceived (i.e., antecedent diversity, focal diversity, and descendant diversity) that can be nicely linked to existing organizational concepts (such as structural inertia, absorptive capacity, niche width, and technological diffusion). Second, viewing a technological system's distinctive set of opportunities in the context of bounded rationality and local search makes the notion of technological opportunities important to consider as well.

The contribution of this chapter is threefold. First, by integrating the growth and evolution of technology into the organization-specific technological niche, we significantly extent the theory, that results in a more realistic model that better resembles the processes actually taking place. Second, by presenting our theory in formal logic, we facilitate the debate and systematic investigation of the role of technology in organization theory. Furthermore, our formal model can also be easily extended (e.g., to include additional stages of development), and our theorems can be easily recast into hypotheses for empirical validation (cf. Chapter 7). Third, by explicitly considering the role of technology, we can further recombine several theory fragments from organizational ecology and evolutionary economics, and reveal some of the fertile grounds that lay between these theories. In doing so, we contribute to the ongoing debate between environmental selection and organizational adaptation, suggesting technology as one of the missing links in this debate.

In the next section of this chapter, we will formalize several of our findings from Chapters 3 and 4 to subsequently integrate them into the theory of the technological niche. That is, in Section 6.3, we will revisit the crowding argument from chapter five and develop theorems that result from our additional assumptions, while Section 6.4 reformulates the status argument in the light of our added knowledge. We will develop our technological diversity argument in Section 6.5, introduce the concept of technological opportunities in Section 6.6, and discuss organizational performance in Section 6.7. Finally, in Section 6.8, we will discuss our findings in the context of the wider academic debate.

6.2 Modeling the Evolution of Technology

In Chapters 3 and 4, we have analyzed the technological niche at the level of a technological component, to elucidate aggregate patterns of technological development. In doing so, we found that technological development within biotechnology displays systemic properties, which can be effectively studied as a technological system composed of a set of interdependent components. Moreover, in Chapter 4, we found that an emerging technology can be characterized by two stages of technological development, namely (1) a seed stage in which a dominant design configuration is established by the technology's stakeholders, and (2) a growth stage during which stakeholders structure themselves according to this dominant design configuration.[22] We found evidence for the existence of these different stages at the component level, and suggest here that these stages can also operate at the system level.

In the current chapter, we concentrate on the system level for two reasons. First, Podolny, Stuart, and Hannan (1996) originally conceive of the organization-specific niche at the system level. To illustrate, they investigate semiconductor technology, which is composed of different technological components (such as photo-masking, doping, etching, PMOS, CMOS, and NMOS technology). Therefore, by concentrating on the system level, we stay closer to their original arguments. Second, concentrating on the system level allows us to develop a general model without getting lost in the details. In a later stage, this model can be easily adapted to study processes at alternative levels of

[22] We acknowledge that additional stages of technological development can be identified, such as a stage of maturity and a stage of decline. However, we are dealing with an emerging technology, which, to our belief, if far from mature. So, in the present setting, these stages are not yet relevant. Moreover, the extension from a two stage model to a four stage model is rather straightforward as the basic ingredients are already there.

analysis. As noted, we represent these findings in a formal way to integrate them into our previously formalized theory fragments. In doing so, we will make use of the background assumptions of Chapter 5 (cf. Appendix E). A description of the logical symbols, predicates, and functions used in the analysis is provided in Appendix G.

What distinguishes between our different stages of technological development is a dominant design configuration of the system's components. That is, on the one hand, the seed stage is characterized by the fact that a dominant design is lacking, implying the existence of multiple design configurations. On the other hand, the growth stage is characterized by the existence of a dominant design configuration that the stakeholders collectively agree upon. To model our different stages of technological development, we need to introduce a temporal dimension. Besides introducing time to distinguish between different stages of technological development, we also include time into our original arguments to demonstrate the ease of extending our logical arguments from the previous chapter. Let $DD(s,t)$ be the predicate that specifies that a dominant design configuration exists in technological system s at time t, and let $G(s,t)$ be the predicate that indicates that technological system s is in the growth stage of development at time t. Now, we are equipped to define our first postulate.

Postulate 6.1

If, at a certain point in time, there exists a dominant design configuration for a technological system, then the period prior to point is called the non-growth (i.e., seed) stage of technological development, and the period after this time point is labeled the growth stage of technological development.

$\mathfrak{N}\ s\ \exists\ t'\ [DD(s,t') \rightarrow \forall t\ [t \geq t' \rightarrow G(s,t) \wedge t' > t \rightarrow \neg G(s,t)]$

Now that we have defined our different stages of technological development, we can define the characteristics of these different stages. Most importantly, in the seed stage of development, technological development is characterized by high uncertainty (Dosi, 1982, 1988). After all, in this stage, due to the existence of multiple design configurations, the future basis of technological development is unknown. In contrast, in the growth stage of technological development, organizations stop investing in alternative configurations, and instead invest their resources and attention in understanding the dominant component configuration (Henderson & Clark, 1990). As a result, the dominant component configuration is refined and elaborated, and progress takes the form of improvements in the components within the framework of a stable configuration (Henderson & Clark, 1990).

This implies that, in the growth stage of development, uncertainty is not only lower than in the seed stage, but also decreases over time (Clark, 1985; Podolny et al., 1996) as organizations gain experience with technological components, and with their combinations and interactions (Fleming, 2001; Mead & Conway, 1980). Hence, over time, organizations learn which components and combinations are useful, and which are better left ignored, which helps them to improve their inventive abilities. This reduces the level of technological uncertainty (Dosi, 1982). So, uncertainty peaks in the seed stage of development and decreases following convergence on a dominant component design configuration (Anderson & Tushman, 1990; Klepper, 1997), as visualized in Figure 6.1. If we let $UC(s,t)$ be the function that specifies the level of uncertainty in technological system s at time t, we then have all the ingredients to formally define the level of uncertainty in the different stages of technological development. In view of that, we formulate our next postulates as follows.

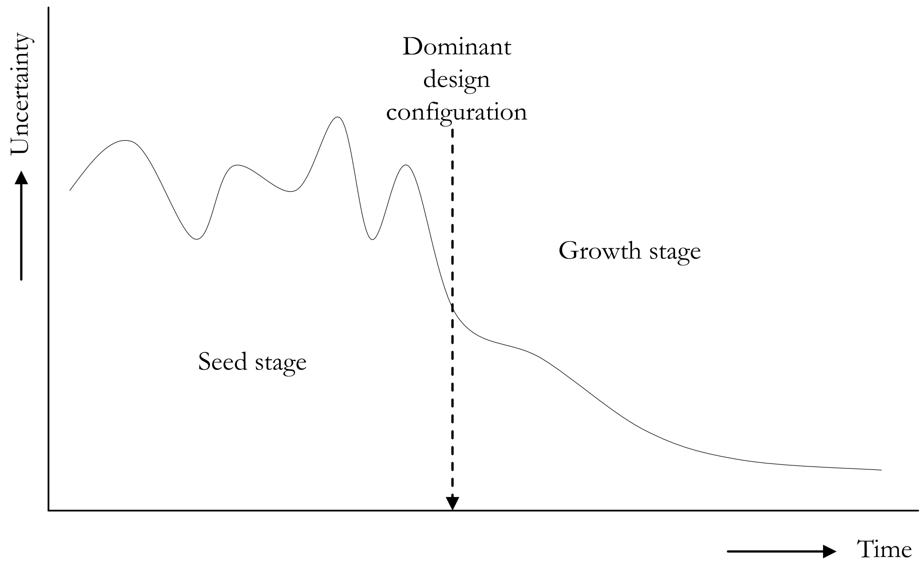

Figure 6.1 Stage-dependent uncertainty

Postulate 6.2

A technological system that is in the non-growth (i.e., seed) stage of technological development has a higher level of uncertainty than a system in the growth stage of technological development.

$\mathfrak{N}\ s,s',t,t'\ [\neg G(s,t) \wedge G(s',t') \rightarrow UC(s,t) > UC(s',t')]$

So, according to this postulate, technological uncertainty is not merely a characteristic of an organization, but also of a technological system. And, as we will demonstrate later in this chapter, this has far reaching consequences for our status argument.

Postulate 6.3

The level of uncertainty in a technological system in the growth stage of technological development decreases over time.

$\mathfrak{N}\, s,t,t' \,[G(s,t) \wedge G(s,t') \wedge t' > t \rightarrow UC(s,t) > UC(s,t')]$

Not only is the level of uncertainty different in alternative technological systems, the technological opportunities within these systems are also different. Technological opportunities refer to variations in the cost and difficulty of innovation in technological systems (Jaffe, 1986). Obviously, these opportunities can change over time and are, to a large extent, dependent upon the system's stage of development. So, different systems present different sets of opportunities. At this moment, we do not know how these opportunities differ precisely. However, the fact that they do already has important implications. We thus make it a formal part of our theory. Let $TS(s)$ be the predicate that indicates that s is a technological system, and let $TO(s,t)$ be the function that specifies the level of opportunities in a technological system s at time t. We can now formulate the following postulate.

Postulate 6.4

All technological systems have a certain amount of technological opportunities at all points in time.

$\mathfrak{N}\, s \,[TS(s) \rightarrow \forall t \,[TO(s,t)]]$

Now that we have developed our postulates regarding the different characteristics of technological systems, we can continue and revisit the theory of the technological niche. This means that we will extent our arguments regarding technological crowding and status with the technological insights by using postulates 6.1 to 6.4, also adding two additional dimensions on the basis of these insights.

6.3 Crowding revisited

To begin with, we need to reformulate our definition of an overlap in technological antecedents to accommodate for the existence of multiple different technological systems. This implies that we need to distinguish between overlap in different technological systems. Hence, we let the predicate $TA(x,y,s,t)$ be the function that specifies the extent to which organization x's shares technological antecedents from technological system s with organization y at time t.

Definition 6.1

The extent to which focal shares technological antecedents from a certain technological system with alter is equal to the cardinality of the intersection of both the organization's sets of antecedents from that technological system, divided by the cardinality of the antecedents of focal from that system.

$$TA(x, y, s, t) = \frac{|A_{xst} \cap A_{yst}|}{|A_{xst}|}$$

where A_{xst} refers to the antecedents of organization x from technological system s at time t, A_{yst} to the antecedents of organization y from technological system s at time t, $|.|$ to the cardinality of a set, and $\cap$ to the intersection of two sets.

Once more, we argue that increasing the shared technological antecedents between two organizations increases the overlap of their technological niches. The only difference is that we, again, need to accommodate for the existence of multiple technological systems. Naturally, the same applies for the relationship between niche overlap and an overlap in technological competencies. So, let $NO(x,y,s,t)$ be the function that specifies the overlap of organization x's technological niche with organization y at time t in technological system s, and let $CO(x,y,s,t)$ be the function that specifies the overlap of organization x's technological competencies in system s with organization y at time t. We can now adjust our postulates accordingly.

Postulate 6.5

The more focal shares technological antecedents from a given technological system with alter, the greater the overlap of focal's technological niche with alter in that same technological system.

$\mathfrak{N}\ x,x',y,y',s,t,t'\ [TA(x,y,s,t) > TA(x',y',s,t') \rightarrow NO(x,y,s,t) > NO(x',y',s,t')]$

Postulate 6.6

The greater (equal) the crowding of focal organization's technological niche with alter at a certain point in time in a certain technological system, the greater (equal) the overlap of focal's technological competencies with alter in that same technological system.

$\mathfrak{N}\ x,x',y,y',s,t,t'\ [NO(x,y,s,t) > NO(x',y',s,t') \rightarrow CO(x,y,s,t) > CO(x',y',s,t') \wedge NO(x,y,s,t) = NO(x',y',s,t') \rightarrow CO(x,y,s,t) = CO(x',y',s,t')]$

In the previous chapter, the effect of an overlap in technological competencies between two organizations was conditional upon whether these organizations actually use these competencies to actively compete with one another. In the current chapter, we also need to take into account the different stages of technological development, as these are characterized by different processes of competition and legitimation. In the seed stage of technological development, (scientific) progress yields a widening pool of design configurations (Dosi, 1988), which results in frequent and deep debates over legitimate methods, problems, and standards of solution (Kuhn, 1996). The environment is thus characterized by high uncertainty and ambiguity as it is unclear which of the several or many designs-configurations will prevail. This implies that competition takes place between alternative design configurations (in an effort to become the dominant design configuration) rather than within the dominant design configuration. It logically follows that, in this stage, competition does not occur between organizations supporting the same design configuration, but rather between organizations supporting alternative, competing, design configurations.

The organization's competencies are directly related to the design configuration that the organization builds upon, so an overlap in technological competencies implies an overlap in design configurations. Accordingly, increasing the overlap in technological competencies increases the degree to which other organizations are betting on the same (part of) the design configuration. This increases the likelihood that this (part of) the design configuration will actually be selected as (or become part of) the dominant one. In other words, crowding reduces the number of alternative designs-configurations and legitimates the supported design configuration. In the seed stage of technological development, crowding thus breeds legitimation (McKendrick, Jaffee, Carroll, & Khessina, 2003; Ruef, 2000), as it strengthens the competitive ability of the supported design configuration vis-à-vis its alternatives. Logically, this implies that non-crowding (Baum & Singh, 1994c) should increase the competitive pressure as it represents the collective of organizations that are backing alternative design configurations in the system. So, when formally relating crowding to organizational performance, we need to control for the effect of non-crowding. Thus, before we continue, we will first develop the basic non-crowding definitions and postulates. Let $NT(x,y,s,t)$ be the degree of non-sharing of technological antecedents between organization x and y in technological system s at time t, which is formally defined below.

Definition 6.2

The non-sharing of technological antecedents between focal and alter in a technological system is equal to the cardinality of the union of the sets of antecedents of both organizations minus the intersection of the sets of antecedents of both organizations, divided by the cardinality of the set of antecedents of focal.

$$NT(x,y,s,t)=\frac{\left|A_{xst}\cup A_{yst'}\right|\setminus\left|A_{xst}\cap A_{yst'}\right|}{\left|A_{xst}\right|}$$

where A_{xst} refers to the antecedents from technological system s of organization x at time t, and A_{yst} reflects the antecedents from technological system s of organization y at time t',

\ denotes set subtraction, |.| refers to the cardinality of a set, ∩ is the intersection of two sets, and ∪ refers to the union of two sets.

Next, let $NN(x,y,s,t)$ be the function that specifies the non-overlap of organization x's technological niche with organization y in system s at time t, and let $NC(x,y,s,t)$ be the non-overlap of organization x's technological competencies with organization y in system s at time t. We now formulate our non-crowding postulates.

Postulate 6.7

The greater (equal) the non-sharing of technological antecedents from a certain technological system between focal and alter at a certain point in time, the (equal) greater the non-overlap of focal's technological niche with alter in that system.

$\mathfrak{N}\ x,x',y,y',s,t,t'\ [NT(x,y,s,t) > NT(x',y',s,t') \rightarrow NN(x,y,s,t) > NN(x',y',s,t') \wedge NT(x,y,s,t) = NT(x',y',s,t') \rightarrow NN(x,y,s,t) = NN(x',y',s,t')]]$

Postulate 6.8

The greater (equal) the non-crowding of focal's technological niche by alter at a certain point in time in a certain technological system, the greater (equal) the non-overlap of focal's technological competencies with alter in that technological system.

$\mathfrak{N}\ x,x',y,y',s,t,t'\ [NN(x,y,s,t) > NN(x',y',s,t') \rightarrow NC(x,y,s,t) > NC(x',y',s,t') \wedge NN(x,y,s,t) = NN(x',y',s,t') \rightarrow NC(x,y,s,t) = NC(x',y',s,t')]$

Because we want to aggregate the effects of crowding and non-crowding to the organization, we need to sum up the effects across the individual technological systems that are in different stages of technological development. Therefore, we will first consider the effects of crowding and non-crowding in the growth stage of development before formalizing the effects on organizational performance.

As mentioned above, the growth stage of technological development starts when the technology's stakeholders (explicitly or implicitly) agree upon a dominant design configuration, which defines the core configuration of the technology's components. A dominant design configuration identifies the principal components and the relationship between them. As a result, competition no longer mainly takes place between alternative design configurations, but rather within the dominant design configuration. That is, organizations stop investing in alternative designs, and instead focus their resources and attention on further developing the configuration outlined in the dominant design (Henderson & Clark, 1990). This suggests that, in the growth stage of technological development, an overlap in technological competencies does result in competition. Regarding the effect of non-crowding in the growth stage of development, since there are no alternative design configurations, all organizations are exclusively focused on exploiting the direction specified in the dominant design configuration. Non-crowding thus implies organizations concentrating on different, complementary parts of the dominant design configuration. Hence, non-crowding has a legitimating effect in the growth stage of technological development. Now that we have outlined the effects of crowding and non-crowding in the different stages of development (see Table 6.1 below), we can aggregate the effects to the organizational level of analysis.

Table 6.1 The effect of technological crowding and non-crowding in different stages of technological development

	Stage of technological development	
	Seed	**Growth**
Technological crowding	Legitimation	Competition
Technological non-crowding	Competition	Legitimation

Due to the differential effects of crowding and non-crowding in the different stages of development, we need to create a switch before we can aggregate the competitive and legitimative effects to the organizational level of analysis. As this is not a substantive part of our theory, we present it formally as an auxiliary assumption.

Auxiliary assumption 6.1

If technological system s is in the seed stage of development at time t, then φ_{st} is 1; otherwise, it is 0.

$\mathfrak{A}\ s,t\ [\neg G(s,t) \rightarrow \varphi_{st} = 1 \wedge G(s,t) \rightarrow \varphi_{st} = 0]$

Next, we introduce dyad-specific competition and legitimation coefficients to allow the strength of competition and legitimation to vary between sets of organizations.

Postulate 6.9

The legitimation coefficient between a pair of organizations maps dyads to the [0,1] interval.

$\mathfrak{P}\ x,y,t\ [0 \leq \lambda_{xyt} \leq 1]$

Postulate 6.10

The competition coefficient between a pair of organizations maps dyads to the [0,1] interval.

$\mathfrak{P}\ x,y,t\ [0 \leq \gamma_{xyt} \leq 1]$

Let the predicate $LP(x,t)$ be the predicate that specifies the legitimative force that is experienced by organization x at time t, and let $CP(x,t)$ indicate the competitive force experienced by organization x at time t. We can now formally aggregate the dyadic (non-

)overlap of technological competencies to competition and legitimation at the organizational level. We do so by the following set of definitions.

Definition 6.5

The legitimative pressure at the organization level is the sum of competencies overlap in systems that are in the non-growth stage of development plus the sum of non-competencies overlap in systems in the growth stage of development, or formally

$$LP(x,t) = \sum_{s}^{S} \varphi_{st} \cdot \sum_{y,\, y \neq x}^{Y} \lambda_{xyt} \cdot CO(x,y,s,t) + \sum_{s}^{S} (1-\varphi_{st}) \cdot \sum_{y,\, y \neq x}^{Y} \lambda_{xyt} \cdot NC(x,y,s,t)$$

where λ_{xyt} is the dyad-specific legitimation coefficient between organizations x and y at time t, S refers to the set of all technological systems, Y refers to the set of all organizations in the population, and φ_{st} is the switch to distinguish between different stages of technological development.

Definition 6.6

The competitive pressure at the organization level is the sum of competencies overlap in systems that are in the growth stage of development plus the sum of non-competencies overlap in systems in the seed stage of development, or formally

$$CP(x,t) = \sum_{s}^{S} (1-\varphi_{st}) \cdot \sum_{y,\, y \neq x}^{Y} \gamma_{xyt} \cdot CO(x,y,s,t) + \sum_{s}^{S} \varphi_{st} \cdot \sum_{y,\, y \neq x}^{Y} \gamma_{xyt} \cdot NC(x,y,s,t)$$

where γ_{xyt} is the dyad-specific competition coefficient between organizations x and y at time t, S refers to the set of all technological systems, Y refers to the set of all organizations in the population, and φ_{st} is the switch to distinguish between different stages of technological development.

Because our theorems will combine the dyadic level of analysis with the organizational level of analysis (e.g., to outline the effect of dyadic niche overlap on organizational performance), we formulate two auxiliary assumptions that allows us to disaggregate the competitive and legitimative pressure at the organizational level into their dyadic components, which effectively allows us to to aggregate the dyadic level to the organizational level at a later stage. Let $LP(x,y,t)$ be the function that specifies the legitimative pressure that organization x experiences from organization y at time t, and let $CP(x,y,t)$ be the function that specifies the legitimative pressure that organization x experiences from organization y at time t.

Auxiliary assumption 6.2

The legitimative pressure at the organizational level equals the sum of the legitimative pressures resulting from two mutually exclusive sets of organizations.

$\mathfrak{A}\ x,y,z,t\ [x \neq y \wedge y \neq z \wedge x \neq z \rightarrow LP(x,t) = LP(x,y,t) + LP(x,z,t)]$

Auxiliary assumption 6.3

The competitive pressure at the organizational level equals the sum of the competitive pressures resulting from two mutually exclusive sets of organizations.

$\mathfrak{A}\ x,y,z,t\ [x \neq y \wedge y \neq z \wedge x \neq z \rightarrow CP(x,t) = CP(x,y,t) + CP(x,z,t)]$

Next, we need to relate the competitive and legitimative forces to organizational performance before we can develop our theorems.

Postulate 6.11

If the legitimative pressure on focal is not greater than the legitimative pressure on alter, and the competitive pressure on focal is greater than the competitive pressure on alter, then the performance of focal is lower than the performance of alter.

$\mathfrak{N}\ x,x',t,t'\ [LP(x,t) \leq LP(x',t') \wedge CP(x,t) > CP(x',t') \rightarrow P(x,t) < P(x',t')]$

Postulate 6.12

If the competitive pressure on focal is not greater than the competitive pressure on alter, and the legitimative pressure on focal is greater than the legitimative pressure on alter, then the performance of focal is higher than the performance of alter.

$\mathfrak{N}\ x,x',t,t'\ [LP(x,t) > LP(x',t') \wedge CP(x,t) \leq CP(x',t') \rightarrow P(x,t) > P(x',t')]$

From these postulates, we can develop the theorems that logically follow from our postulates using a modified version of a so-called truth table (cf. Appendix H). In a truth table, essentiall all combinations of the statements of interest are specified, by using all statements (e.g., $LP(x,t) > LP(x',t')$) as columns, and listing all possible combinations of truth values for these statements in rows (i.e., develop all possible scenarios), and subsequently indicating whether or not the combined statements are true. For the sake of brevity, we exclude the scenarios that are false, and thus only list a modified partial-truth table in Appendix H.

Theorem 6.1

If (a) the technological system remains in the seed stage of development, (b) the dyadic overlap of focal's technological niche is greater than alter's, (c) the dyadic non-overlap of focal's technological niche is not greater than alter's, (d) focal's legitimation coefficient is not smaller than alter's, (e) focal's competition coefficient is not greater than alter's, (f) focal's remaining legitimative pressure is not smaller than alter's, and (f) focal's remaining competitive pressure is not greater than alter's, then the performance of focal is greater than the performance of alter.

$\mathfrak{P}\ x,x',y,y',s,t,t'\ [\neg G(s,t) \wedge \neg G(s,t') \wedge NO(x,y,s,t) > NO(x',y',s,t') \wedge NN(x,y,s,t) \leq NN(x',y',s,t') \wedge \lambda_{xyt} \geq \lambda_{x'y't'} \wedge \gamma_{xyt} \leq \gamma_{x'y't'} \wedge \forall\ z,z'\ [x \neq y \wedge y \neq z \wedge y' \neq z' \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t')] \rightarrow P(x,t) > P(x',t')]$

Proof for this theorem is provided by auxiliary assumption 6.1 to 6.3, definition 6.5 and 6.6, and postulate 6.6, 6.8, and 6.12 (see Appendix J).

Theorem 6.2

If (a) the technological system remains in the seed stage of development, (b) the dyadic overlap of focal's technological niche is not smaller than alter's, (c) the dyadic non-overlap of focal's technological niche is not greater than alter's, (d) focal's legitimation coefficient is greater than alter's, (e) focal's competition coefficient is not greater than alter's, (f) focal's remaining legitimative pressure is not smaller than alter's, and (f) focal's remaining competitive pressure is not greater than alter's, then the performance of focal is greater than the performance of alter.

$\mathfrak{P}\ x,x',y,y',s,t,t'\ [\neg G(s,t) \wedge \neg G(s,t') \wedge NO(x,y,s,t) \geq NO(x',y',s,t') \wedge NN(x,y,s,t) \leq NN(x',y',s,t') \wedge \lambda_{xyt} > \lambda_{x'y't'} \wedge \gamma_{xyt} \leq \gamma_{x'y't'} \wedge \forall\ z,z'\ [x \neq y \wedge y \neq z \wedge y' \neq z' \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t')] \rightarrow P(x,t) > P(x',t')]$

Proof for this theorem is provided by auxiliary assumption 6.1 to 6.3, definition 6.5 and 6.6, and postulate 6.6, 6.8, and 6.12 (see Appendix J).

Theorem 6.3

If (a) the technological system remains in growth stage of development, (b) the dyadic overlap of focal's technological niche is greater than alter's, (c) the dyadic non-overlap of focal's technological niche is not greater than alter's, (d) focal's legitimation coefficient is not greater than alter's, (e) focal's competition coefficient is not smaller than alter's, (f) focal's remaining legitimative pressure is not greater than alter's, and (f) focal's remaining competitive pressure is not smaller than alter's, then the performance of focal is smaller than the performance of alter.

$\mathfrak{P}\ x,x',y,y',d,t,t'\ [G(s,t) \wedge G(s,t') \wedge NO(x,y,s,t) > NO(x',y',s,t') \wedge NN(x,y,s,t) \leq NN(x',y',s,t') \wedge \lambda_{xyt} \leq \lambda_{x'y't'} \wedge \gamma_{xyt} \geq \gamma_{x'y't'} \wedge \forall\ z,z'\ [x \neq y \wedge y \neq z \wedge y' \neq z' \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t')] \rightarrow P(x,t) < P(x',t')]$

Proof for this theorem is provided by auxiliary assumption 6.1 to 6.3, definition 6.5 and 6.6, and postulate 6.6, 6.8, and 6.11 (see Appendix J).

Theorem 6.4

If (a) the technological system remains in the growth stage of development, (b) the dyadic overlap of focal's technological niche is not smaller than alter's, (c) the dyadic non-overlap of focal's technological niche is not greater than alter's, (d) focal's legitimation coefficient is not greater than alter's, (e) focal's competition coefficient is greater than alter's, (f) focal's remaining legitimative pressure is not greater than alter's, and (f) focal's remaining competitive pressure is not smaller than alter's, then the performance of focal is smaller than the performance of alter.

$\mathfrak{P}\, x,x',y,y',s,t,t'\ [G(s,t) \wedge G(s,t') \wedge NO(x,y,s,t) \geq NO(x',y',s,t') \wedge NN(x,y,s,t) \leq NN(x',y',s,t') \wedge \lambda_{xyt} \leq \lambda_{x'y't'} \wedge \gamma_{xyt} > \gamma_{x'y't'} \wedge \forall\, z,z'\ [x \neq y\ \wedge y \neq z\ \wedge y' \neq z'\ \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t')] \rightarrow P(x,t) < P(x',t')]$

Proof for this theorem is provided by auxiliary assumption 6.1 to 6.3, definition 6.5 and 6.6, and postulate 6.6, 6.8, and 6.11 (see Appendix J).

Theorem 6.5

If (a) the technological system remains in the seed stage of development, (b) the dyadic overlap of focal's technological niche is not greater than alter's, (c) the dyadic non-overlap of focal's technological niche is greater than alter's, (d) focal's legitimation coefficient is not greater than alter's, (e) focal's competition coefficient is not smaller than alter's, (f) focal's remaining legitimative pressure is not greater than alter's, and (f) focal's remaining competitive pressure is not smaller than alter's, then the performance of focal is smaller than the performance of alter.

$\mathfrak{P}\, x,x',y,y',s,t,t'\ [\neg G(s,t) \wedge \neg G(s,t') \wedge NO(x,y,s,t) \leq NO(x',y',s,t') \wedge NN(x,y,s,t) > NN(x',y',s,t') \wedge \lambda_{xyt} \leq \lambda_{x'y't'} \wedge \gamma_{xyt} \geq \gamma_{x'y't'}\ \forall\, z,z'\ [x \neq y\ \wedge y \neq z\ \wedge y' \neq z'\ \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t')] \rightarrow P(x,t) < P(x',t')]$

Proof for this theorem is provided by auxiliary assumption 6.1 to 6.3, definition 6.5 and 6.6, and postulate 6.6, 6.8, and 6.11 (see Appendix J).

Theorem 6.6

If (a) the technological system remains in the seed stage of development, (b) the dyadic overlap of focal's technological niche is not greater than alter's, (c) the dyadic non-overlap of focal's technological niche is not smaller than alter's, (d) focal's legitimation coefficient is not greater than alter's, (e) focal's competition coefficient is greater than alter's, (f) focal's remaining legitimative pressure is not greater than alter's, and (f) focal's remaining competitive pressure is not smaller than alter's, then the performance of focal is smaller than the performance of alter.

$\mathfrak{P}\ x,x',y,y',s,t,t'\ [\neg G(s,t) \wedge \neg G(s,t') \wedge NO(x,y,s,t) \leq NO(x',y',s,t') \wedge NN(x,y,s,t) \geq NN(x',y',s,t') \wedge \lambda_{xyt} \leq \lambda_{x'y't'} \wedge \gamma_{xyt} > \gamma_{x'y't'}\ \forall\ z,z'\ [x \neq y \ \wedge y \neq z \ \wedge y' \neq z' \ \wedge LP(x,z,t) \leq LP(x',z',t') \wedge CP(x,z,t) \geq CP(x',z',t')] \rightarrow P(x,t) < P(x',t')]$

Proof for this theorem is provided by auxiliary assumption 6.1 to 6.3, definition 6.5 and 6.6, and postulate 6.6, 6.8, and 6.11 (see Appendix J).

Theorem 6.7

If (a) the technological system remains in the growth stage of development, (b) the dyadic overlap of focal's technological niche is not greater than alter's, (c) the dyadic non-overlap of focal's technological niche is greater than alter's, (d) focal's legitimation coefficient is not smaller than alter's, (e) focal's competition coefficient is not greater than alter's, (f) focal's remaining legitimative pressure is not smaller than alter's, and (f) focal's remaining competitive pressure is not greater than alter's, then the performance of focal is greater than the performance of alter.

$\mathfrak{P}\ x,x',y,y',s,t,t'\ [G(s,t) \wedge G(s,t') \wedge NO(x,y,s,t) \leq NO(x',y',s,t') \wedge NN(x,y,s,t) > NN(x',y',s,t') \wedge \lambda_{xyt} \geq \lambda_{x'y't'} \wedge \gamma_{xyt} \leq \gamma_{x'y't'} \wedge \forall\ z,z'\ [x \neq y \ \wedge y \neq z \ \wedge y' \neq z' \ \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t')] \rightarrow P(x,t) > P(x',t')]$

Proof for this theorem is provided by auxiliary assumption 6.1 to 6.3, definition 6.5 and 6.6, and postulate 6.6, 6.8, and 6.12 (see Appendix J).

Theorem 6.8

If (a) the technological system remains in the growth stage of development, (b) the dyadic overlap of focal's technological niche is not greater than alter's, (c) the dyadic non-overlap of focal's technological niche is not smaller than alter's, (d) focal's legitimation coefficient is greater than alter's, (e) focal's competition coefficient is not greater than alter's, (f) focal's remaining legitimative pressure is not smaller than alter's, and (f) focal's remaining competitive pressure is not greater than alter's, then the performance of focal is greater than the performance of alter.

$\mathfrak{P}\ x,x',y,y',s,t,t'\ [G(s,t) \wedge G(s,t') \wedge NO(x,y,s,t) \leq NO(x',y',s,t') \wedge NN(x,y,s,t) \geq NN(x',y',s,t') \wedge \lambda_{xyt} > \lambda_{x'y't'} \wedge \gamma_{xyt} \leq \gamma_{x'y't'} \wedge \forall\ z,z'\ [x \neq y \ \wedge y \neq z \ \wedge y' \neq z' \ \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t')] \rightarrow P(x,t) > P(x',t')]$

Proof for this theorem is provided by auxiliary assumption 6.1 to 6.3, definition 6.5 and 6.6, and postulate 6.6, 6.8, and 6.12 (see Appendix J).

This concludes our (non-)crowding argument, which is graphically displayed in Figure 6.2. Next, we consider the consequences for our arguments when accommodating for the existence of multiple technological systems with multiple stages of technological development.

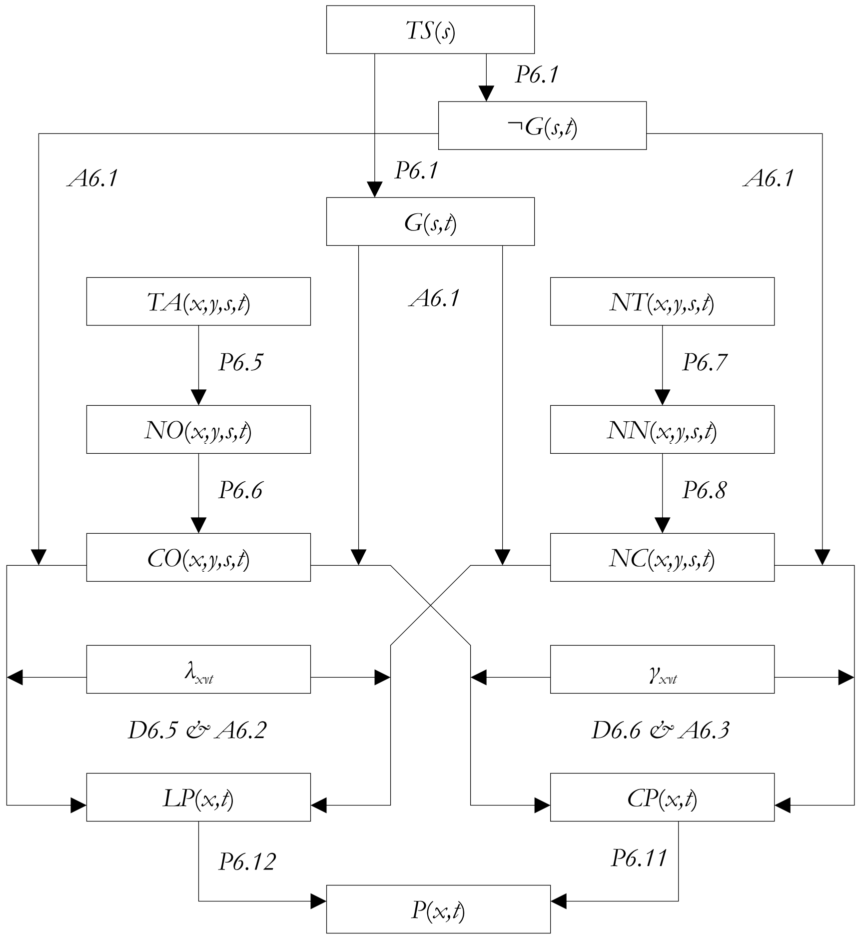

Figure 6.2 Argumentative structure crowding

6.4 Status revisited

As mentioned in Chapter 5, status is used by resource controllers when the quality of technology cannot be objectively determined due to the uncertainty surrounding the technology. Moreover, in situations of relative certainty, resource controllers rely less on status as the actual quality can be (partly) observed. Thus, the effect of status or actual quality is mediated by the level of uncertainty surrounding the technology.

Because technological uncertainty is to a large extent a property of a technological system, we claim that status is tied to specific technological systems. After all, it is only logical to assume that resource controllers only use the organization's past quality or status that is relevant to the focal technological system. To illustrate this with an example, it is highly unlikely that a high-status car manufacturer can effectively utilize its status to mobilize resources in biotechnology. Even though a large part of our argumentative structure essentially remains the same, we have to adapt all definitions and postulates to allow for the existence of multiple technological systems and different stages of technological development. Recall from the previous chapter that status is defined as the organization's share of acts of deference from actors in the system, and that quality is defined as the organization's share of the system's technology. Let $S(x,s,t)$ be the predicate that specifies the level of status that organization x has in technological system s at time t, and let $Q(x,s,t)$ be the technological quality that organization has in system s at time t. Now, we can formally define quality and status as follows.

Definition 6.7

The technological status of an organization in a technological system at a certain time is the organization's share of the total acts of deference from all organizations active in that system.

$$S(x,s,t)=\frac{DA_{xst}}{\sum_{y}^{Y} DA_{yst}}$$

where DA_{xst} refers to the acts of deference that organization x receives from system s at time t, DA_{yst} to acts of deference that organization y receives from system s at time t, and Y to all organizations in the population.

Definition 6.8

The technological quality of an organization in a technological system at a certain time is the organization's share of the total technology in that system.

$$Q(x,s,t)=\frac{T_{xst}}{\sum_{y}^{Y} T_{yst}}$$

where T_{xst} refers to the share of technology in system s that is owned by organization x at time t, T_{yst} to the share of technology that is owned by organization y in technological system s at time t, and Y to all organizations in the population.

Again, we assume that the effect of quality and status on the perceived quality of an organization is mediated by uncertainty. However, instead of uncertainty merely being an organizational characteristic, we now assume that uncertainty is a system-specific feature as well (Podolny et al., 1996). Let us also assume that the level of uncertainty is a ratio between 0 (complete certainty) to 1 (complete uncertainty). We assume that the extremes (i.e., complete certainty and complete uncertainty) never occur, because the future is never completely certain (i.e., it cannot be precisely predicted) or uncertain (i.e., certain things do remain the same). This is represented by the following auxiliary assumption.

Postulate 6.13

The uncertainty function of a technological system maps system and time points to the ⟨0,1⟩ interval.

$\mathfrak{P}\ s,t\ [0 < UC(s,t) < 1]$

Using postulate 6.13, we can formally define the functional relationship between an organization's quality, status and its perceived quality. Let $Q(x,s,t)$ be the function that specifies organization *x*'s technological quality in system *s* at time *t*, let $S(x,s,t)$ be organization *x*'s status in system *s* at time *t*, and let $PQ(x,s,t)$ be the perceived quality of organization *x*'s technology in technological system *s* at time *t*.

Definition 6.9

The perceived quality of an organization in a technological system can be defined as

$$PQ(x,s,t) = (1 - UC(s,t)) \cdot Q(x,s,t) + UC(s,t) \cdot S(x,s,t)$$

Next, we link the organization's perceived quality to its ability to mobilize resources within a technological system. Let $MR(x,s,t)$ be organization *x*'s ability to mobilize resources in technological system *s* at time *t*. We can now define our next postulate accordingly.

Postulate 6.14

The greater the perceived quality of an organization's technology within a technological system, the greater is that organization's ability to mobilize resources.

$\mathfrak{N}\ x,x',s,t,t'\ [PQ(x,s,t) > PQ(x',s,t') \rightarrow MR(x,s,t) > MR(x',s,t')]$

We need to aggregate the ability to mobilize resources within a technological system to the organizational level before we can formulate propositions regarding the consequences for the organization's performance.

Definition 6.10

The organization's ability to mobilize resources is the sum of the abilities to mobilize resources in the technological systems in which the organization is active.

$$MR(x,t) = \sum_{S=1}^{s=S} MR(x,s,t)$$

Now, we can continue at the organizational level and relate the ability to mobilize resources to the mortality of the organization, implying that, after our next postulate, we are fully equipped to proof our theorems.

Postulate 6.15

The greater the organization's ability to mobilize resources, the greater is the performance of that same organization.

$\mathfrak{N}\ x,x',t,t'\ [MR(x,t) > MR(x',t') \rightarrow\ P(x,t) > P(x',t')]$

Again, we will use a modified truth table (cf. Appendix I) to develop the theorems that logically follow from our collection of postulates, assumptions, and definitions.

Theorem 6.9

If (a) the uncertainty within a technological system remains equal whilst (b) the quality of focal is greater than the quality of alter, (c) the technological status of focal is not smaller than the status of alter, and (d) focal's ability to mobilize resources in the remaining technological systems is not smaller than alter's ability to do so, then the performance of focal is greater than the performance of alter.

$\mathfrak{P}\ x,x',s,t,t'\ [UC(s,t) = UC(s,t') \wedge Q(x,s,t) > Q(x',s,t') \wedge S(x,s,t) \geq S(x,s,t')\ \wedge \forall\ z\ [s \neq z\ \wedge \sum_z MR(x,z,t) \geq \sum_z MR(x',z,t')]\ \rightarrow\ P(x,t) > P(x',t')]$

Proof for this theorem is provided by definition 6.9 and 6.10, and postulates 6.14 and 6.15 (see Appendix J).

Theorem 6.10

If (a) the uncertainty within a technological system remains equal whilst (b) the technological quality of focal is not smaller than the quality of alter, (c) the status of focal is greater than the status of alter, and (d) focal's ability to mobilize resources in the remaining technological systems is not smaller than alter's ability to do so, then the performance of focal is greater than the performance of alter.

$\mathfrak{P}\ x,x',s,t,t'\ [UC(s,t) = UC(s,t') \wedge Q(x,s,t) \geq Q(x',s,t') \wedge S(x,s,t) > S(x',s,t') \wedge \forall\ z\ [s \neq z\ \wedge \sum_z MR(x,z,t) \geq \sum_z MR(x',z,t')] \rightarrow\ P(x,t) > P(x',t')]$

Proof for this theorem is provided by definition 6.9 and 6.10, and postulates 6.14 and 6.15 (see Appendix J).

Theorem 6.11

When (a) the uncertainty for focal is lower than the uncertainty for alter, (b) the technological quality of focal is not greater than the quality of alter, (c) the status of focal is not greater than the status of alter, (d) the quality of focal is smaller than its status, and (e) focal's ability to mobilize resources in the remaining technological systems is not greater than alter's ability to do so, then the performance of focal is smaller than the performance of alter.

$$\mathfrak{P}\, x,x',s,t,t'\ [UC(s,t) < UC(s,t') \wedge Q(x,s,t) \leq Q(x',s,t') \wedge S(x,s,t) \leq S(x',s,t') \wedge Q(x,s,t) < S(x,s,t) \wedge \forall\, z\ [s \neq z \wedge \textstyle\sum_z MR(x,z,t) \leq \sum_z MR(x',z,t')] \rightarrow P(x,t) < P(x',t')]$$

Proof for this theorem is provided by definition 6.9 and 6.10, and postulates 6.14 and 6.15 (see Appendix J).

Theorem 6.12

When (a) the uncertainty for focal is greater than the uncertainty for alter, (b) the technological quality of focal is not greater than the quality of alter, (c) the status of focal is not greater than the status of alter, (d) the quality of focal is greater than its status, and (e) focal's ability to mobilize resources in the remaining technological systems is not greater than alter's ability to do so, then the performance of focal is smaller than the performance of alter.

$$\mathfrak{P}\, x,x',s,t,t'\ [UC(s,t) > UC(s,t') \wedge Q(x',s,t') \leq Q(x',s,t) \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) > S(x,s,t) \wedge \forall\, z\ [s \neq z \wedge \textstyle\sum_z MR(x,z,t) \leq \sum_z MR(x',z,t')] \rightarrow P(x,t) < P(x',t')]$$

Proof for this theorem is provided by definition 6.9 and 6.10, and postulates 6.14 and 6.15 (see Appendix J).

Next, we consider what happens when taking into account the different stages of technological development.

Theorem 6.13

When (a) the technological quality and status of an organization do not decrease, (b) while its technological quality is higher than its status and (c) the technological system is in the growth stage of development, and (e) the organization's ability to mobilize resources in the remaining technological systems does not decrease, then increasing time increases the organization's performance.

$$\mathfrak{P}\, x,s,t,t'\ [G(s,t) \wedge t' > t \wedge Q(x,s,t) \leq Q(x,s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) > S(x,s,t) \wedge \forall\, z\ [s \neq z \wedge \textstyle\sum_z MR(x,z,t) \leq \sum_z MR(x,z,t')] \rightarrow P(x,t) < P(x,t')]$$

Proof for this theorem is provided by definition 6.9 and 6.10, and postulates 6.3, 6.14, and 6.15 (see Appendix J).

Theorem 6.14

When (a) the technological quality and status of an organization do not decrease whilst (b) its technological quality is higher than its status, and (c) the organization's ability to mobilize resources in the remaining technological systems does not decrease, then a transition of the technological system from the seed into the growth stage of development increases the organization's performance.

$$\mathfrak{P}\, x,s,t,t'\, [\neg G(s,t) \wedge G(s,t') \wedge Q(x,s,t) \leq Q(x,s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) > S(x,s,t) \wedge \forall\, z\, [s \neq z \wedge \textstyle\sum_z MR(x,z,t) \leq \sum_z MR(x,z,t')] \rightarrow P(x,t) < P(x,t')]$$

Proof for this theorem is provided by definition 6.9 and 6.10, and postulates 6.2, 6.14, and 6.15 (see Appendix J).

Theorem 6.15

When (a) the technological quality and status of an organization do not increase whilst (b) its technological quality is lower than its status, (c) the technological system is in the growth stage of development, and (d) the organization's ability to mobilize resources in the remaining technological systems does not decrease, then increasing time decreases the organization's performance.

$$\mathfrak{P}\, x,s,t,t'\, [G(s,t) \wedge t > t' \wedge Q(x,s,t) \leq Q(x,s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) < S(x,s,t) \wedge \forall\, z\, [s \neq z \wedge \textstyle\sum_z MR(x,z,t) \leq \sum_z MR(x,z,t')] \rightarrow P(x,t) < P(x,t')]$$

Proof for this theorem is provided by definition 6.9 and 6.10, and postulates 6.3, 6.14, and 6.15 (see Appendix J).

Theorem 6.16

When (a) the technological quality and status of an organization do not increase whilst (b) its technological quality is lower than its status, and (c) the organization's ability to mobilize resources in the remaining technological systems does not decrease, then a transition of the technological system from the seed into the growth stage of development decreases the organization's performance.

$$\mathfrak{P}\, x,s,t,t'\, [\neg G(s,t') \wedge G(s,t) \wedge Q(x,s,t) \leq Q(x,s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) < S(x,s,t) \wedge \forall\, z\, [s \neq z \wedge \textstyle\sum_z MR(x,z,t) \leq \sum_z MR(x,z,t')] \rightarrow P(x,t) < P(x,t')]$$

Proof for this theorem is provided by definition 6.9 and 6.10, and postulates 6.2, 6.14, and 6.15 (see Appendix J).

This concludes our status argument, which is displayed in Figure 6.3. Relaxing the assumption of a single homogenous technological system not only requires reformulating the arguments of crowding and status, it also points to yet another dimension of the technological niche, namely diversity, which we will investigate in more detail in the next section.

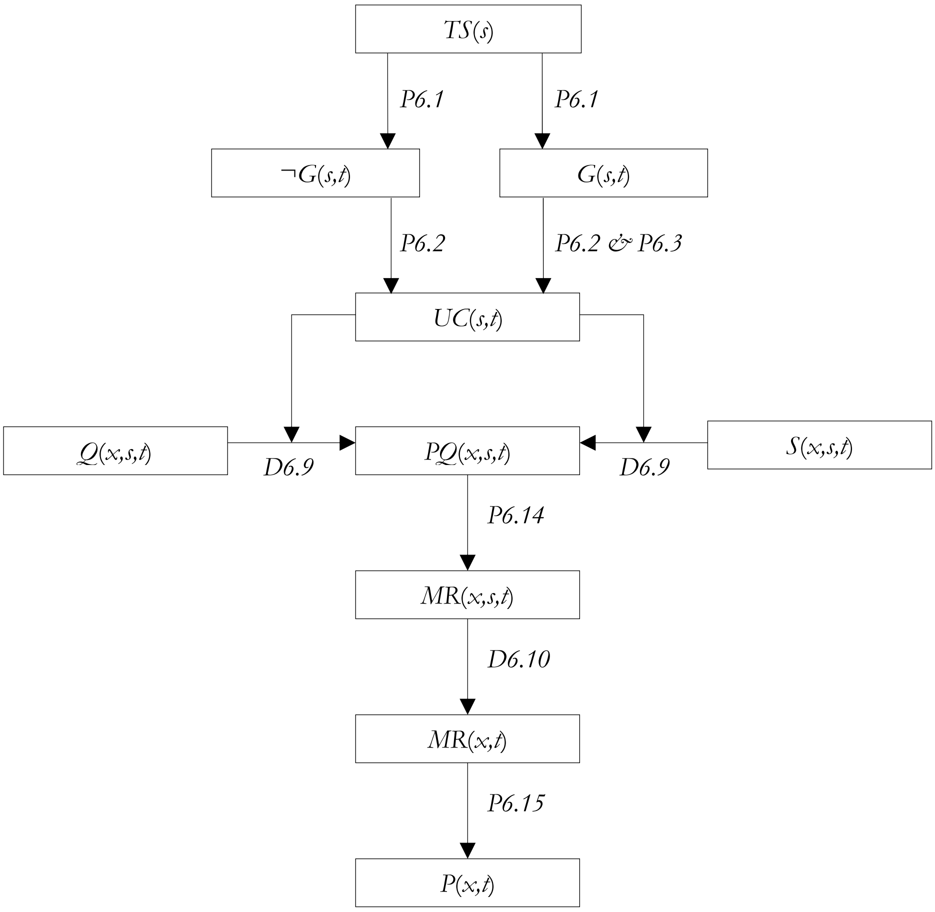

Figure 6.3 Argumentative structure status

6.5 Technological diversity

In analogue to the biological question "Why are there so many kinds of animals?" (Hutchinson, 1959: 145), organizational ecologists have been concerned with the question "Why are there so many kinds of organizations?" (Hannan & Freeman, 1977: 929). Diversity also is a central notion in evolutionary economics (Nelson & Winter, 1982), where it is considered to form a crucial condition for the creation of inventions, and where it is connected to the idea that diversity is the ultimate source of novelty. In light of this, it comes as no surprise that diversity also plays an important role in technological development at the organizational level of analysis. As we have seen in Chapter 4, diversity plays an intricate role in technological development at aggregate levels of analysis. When considering the existence of multiple technological systems in conjunction with technological lineage (cf. Figure 1.3) at the organizational level of analysis, again, three dimensions of technological diversity naturally emerge, namely: (1) focal diversity – i.e., the extent to which an organization's developments take place in different technological systems, (2) antecedent diversity – i.e., the extent to which an organization's knowledge comes from different technological systems, and (3) descendant diversity – i.e., the extent to which an organization's technology is diffused among different technological systems. Next, we define these dimensions of technological diversity in a formal way.

Definition 6.11

An organization's focal diversity is defined as

$$D_{xft} = \sum_{s}^{S} \tau_{xst} \ln(1/\tau_{xst})$$

where τ_{xst} refers to the share of focal technology from organization x that comes from technological system s at time t, and S to the set of all technological systems.

Definition 6.12

The organization's antecedent diversity is defined as

$$D_{xat} = \sum_{s}^{S} \theta_{xst} \ln(1/\theta_{xst})$$

where θ_{xst} is the share of technological antecedents of organization x at time t that come from technological system s, and S refers to the set of all technological systems.

Definition 6.13

The organization's descendant diversity is defined as

$$D_{xdt} = \sum_{s}^{S} \upsilon_{xst} \ln(1/\upsilon_{xst})$$

where υ_{xst} is the share of technological descendants of organization x at time t that come from technological system s, and S refers to the set of all technological systems.

Next, we will explore what the effects are of these different dimensions of diversity on organizational performance. First, regarding focal diversity, developments in different technological systems essentially refers to the width or scope of the technology that the organization possesses. Hence, it represents the organization's realized technological niche, and thus pertains to the distinction between technological generalism and specialism (Hannan et al., 2007). Following the principle of allocation, there is a tradeoff between niche width and strength of appeal (Hannan & Freeman, 1977).[23] As a result, due to the cost of carrying slack, specialists do better in stable environments, while generalists are assumed to do better in changing environments (Hannan & Freeman, 1977; Péli, 1997). So, according to ecological logic, contingent upon environmental conditions, focal diversity can have both a positive and a negative effect on organizational performance and mortality.

This dual role of focal diversity also becomes apparent when contemplating evolutionary economics logic. According to this literature, focal diversity provides alternatives that enhance the organization's flexibility, hereby preventing path dependence (Stirling, 2007). However, added value will only be created when the organization is able to generate spillovers between the competencies it holds in different systems (Nesta & Saviotti, 2005). The costs of generating spillovers between competencies from unrelated systems increase substantially (Ahuja & Katila, 2004; Fleming & Sorenson, 2001), and too much diversity can thus hold the organization at a competitive disadvantage.

This twin role of technological diversity also becomes apparent when we consider the effect of antecedent diversity on organizational performance. Antecedent diversity refers to the diversity of the organization's knowledge base. The more diverse this knowledge base, the higher the organization's recombination potential. After all, the co-existence of diverse knowledge elicits the sort of learning that yields innovation (Simon, 1985). It also connects to the notion of absorptive capacity, which is a function of the organization's prior related knowledge (Cohen & Levinthal, 1990; Van den Bosch, Volberda, & de Boer, 1999; Zahra & George, 2002). However, because any knowledge component can be combined with every other component, the organization's recombination potential grows explosively (Fleming, 2001; Weitzman, 1996). And, as a result, organizations have no more than an infinitesimal understanding of the possible combinations and relationships (Fleming, 2001). This requires them to recombine locally, from a limited set of well-known components (Nelson and Winter, 1982; Sahal, 1985, Utterback, 1996; Fleming, 2001). That is, too much antecedent diversity decreases the probability that additional diversity can be interpreted in a sensible manner (Levinthal and March, 1993; Nooteboom, 2000).

The diversity of the organizations technological descendants indicates the extent to which organizations from different technological systems use the organization's technology as input in their recombination process. It thus reflects the degree to which the organization's technology is diffused throughout the technological landscape. Again, this is a two-edged sword. The reason is that a direct technological tie cannot be interpreted in a unique sense (Podolny et al., 1996). On the one hand, it suggests that the

[23] Péli (1997) has formalized niche theory in first-order logic, and Hannan, Pólos, and Carroll (2007) have done so in non-monotonic logic.

organization's technology contributes to a broad array of developments, thus legitimating its technology. On the other hand, it also implies that more organizations are technological proximate to the organization, hereby increasing the competitive potential. So, in a similar vein, the effect of descendant diversity on organizational performance is contingent upon the precise circumstances.

From the discussion above, it becomes clear that the effect of diversity on organizational performance is conditional upon organizational and environmental characteristics. Hence, explicitly modeling the effects of the different dimensions of technological diversity on organizational performance is a rather involved endeavor. Undeniably, a one-size-fits-all strategy is not appropriate, as each dimension of technological diversity connects to numerous arguments in the extant literature and, as such, deserves a separate investigation. So, instead of fully explicating all the potential effects separately, we develop a general model where each dimension of diversity can both have a positive or a negative effect on organizational performance, and leave it to future work to connect these dimensions to the appropriate constructs and concepts in the different literatures. An advantage of this approach is that it also leaves the door open for any literature that might be relevant to the research question at hand.

Let $D(x,d,t)$ be the predicate the specifies the diversity of organization x's dimension d at time t, let $M(x,d,t)$ be the predicate that refers to the effect of diversity of organization x's dimension d at time t, let $Opp(x,t)$ represent the number of opportunities that organization x has at time t, and let $Cost(x,t)$ be the predicate that specifies organization x's costs at time t. We can now formulate our auxiliary assumptions and postulates.

Auxiliary assumption 6.4

An organization's technological diversity consists of three dimensions, namely focal diversity, antecedent diversity, and descendant diversity.

$\mathfrak{A}\ x,d,t\ [D(x,d,t) \rightarrow d = antecedent \vee d = focal \vee d = descendant]$

The above assumption specifies that the organization's technological diversity has three dimensions. Because each of these dimensions can imply either opportunities or threats for the organization, we accommodate for both scenarios. We thus define a time-, organization-, and dimension-specific multiplier that allows the magnitude of the effect to differ between organizations, dimensions, and over time.

Postulate 6.16

Each dimension of an organization's technological diversity has a multiplier that ranges between the values -1 and 1.

$\mathfrak{N}\ x,d,t\ [D(x,d,t) > 0 \rightarrow -1 \leq M(x,d,t) \leq 1]$

Depending on the value of this multiplier, the effect of diversity can either be positive (i.e., more opportunities) or negative (i.e., more threats) for the organization. Next, we formulate the effects of changing the level of diversity or the value of the multiplier formally using the following postulates.

Postulate 6.17
When (a) focal's diversity multiplier is greater than zero, (b) focal's diversity multiplier is not smaller than alter's diversity multiplier, and (c) the technological diversity of focal is greater than the diversity of alter, than focal's opportunities are greater than alter's opportunities.
$\mathfrak{N}\ x,x',d,t,t'\ [D(x,d,t) > D(x',d,t') \wedge M(x,d,t) \geq M(x',d,t') \wedge M(x,d,t) > 0 \rightarrow$
$Opp(x,t) > Opp(x',t')]$

Postulate 6.18
When (a) alter's diversity multiplier is smaller than zero, (b) focal's diversity multiplier is not greater than alter's diversity multiplier, and (c) the technological diversity of focal is greater than the diversity of alter, than focal's costs are greater than alter's costs.
$\mathfrak{N}\ \forall x,x',d,t,t'\ [D(x,d,t) > D(x',d,t') \wedge M(x,d,t) \leq M(x',d,t') \wedge M(x',d,t') < 0 \rightarrow$
$Cost(x,t) > Cost(x',t')]$

Postulate 6.19
When (a) alter's diversity multiplier is greater than zero, (b) focal's diversity multiplier is greater than alter's diversity multiplier, and (c) the technological diversity of focal is not smaller than the diversity of alter, than focal's opportunities are greater than alter's opportunities.
$\mathfrak{N}\ x,x',d,t,t'\ [D(x,d,t) \geq D(x',d,t') \wedge M(x,d,t) > M(x',d,t') \wedge M(x',d,t') > 0 \rightarrow$
$Opp(x,t) > Opp(x',t')]$

Postulate 6.20
When (a) alter's diversity multiplier is smaller than zero, (b) focal's diversity multiplier is smaller than alter's diversity multiplier, and (c) the technological diversity of focal is not smaller than the diversity of alter, than focal's costs are greater than alter's costs.
$\mathfrak{N}\ x,x',r,t,t'\ [D(x,d,t) \geq D(x',d,t') \wedge M(x,d,t) < M(x',d,t') \wedge M(x',d,t') < 0 \rightarrow$
$Cost(x,t) > Cost(x',t')]$

Next, we can relate changes in opportunities and threats to the organization's performance in the following manner.

Postulate 6.21

If the opportunities of focal are greater than alter's opportunities while the costs of focal are not greater than alter's, then focal's performance is greater than alter's performance.

$\mathfrak{N}\ x,x',r,t,t'\ [Cost(x,t) \leq Cost(x',t') \wedge Opp(x,t) > Opp(x',t') \rightarrow P(x,t) > P(x',t')]$

Postulate 6.22

If the costs of focal are smaller than alter's costs while the opportunities of focal are not smaller than alter's, then focal's performance is greater than alter's performance.

$\mathfrak{N}\ x,x',r,t,t'\ [Cost(x,t) < Cost(x',t') \wedge Opp(x,t) \geq Opp(x',t') \rightarrow P(x,t) > P(x',t')]$

Now, we are fully equipped to formulate the theorems that naturally follow from our postulates, definitions, and assumptions.

Theorem 6.17

When (a) alter's diversity multiplier is greater than zero, (b) alter's diversity multiplier is not greater than focal's multiplier, and (c) focal's technological diversity is greater than alter's technological diversity, then focal's performance is greater than alter's performance.

$\mathfrak{P}\ x,x',d,t,t'\ [D(x,d,t) > D(x',d,t') \wedge M(x,d,t) \geq M(x',d,t') \wedge M(x',d,t') > 0 \rightarrow P(x,t)$
$> P(x',t')]$

Proof for this theorem is provided by postulate 6.17 and 6.21 (see Appendix J).

Theorem 6.18

When (a) alter's diversity multiplier is smaller than zero, (b) alter's diversity multiplier is not smaller than focal's multiplier, and (c) focal's technological diversity is greater than alter's technological diversity, then focal's performance is smaller than alter's performance.

$\mathfrak{P}\ x,x',d,t,t'\ [D(x,d,t) > D(x',d,t') \wedge M(x,d,t) \leq M(x',d,t') \wedge M(x',d,t') < 0 \rightarrow$
$P(x,t) < P(x',t')]$

Proof for this theorem is provided by postulate 6.18 and 6.22 (see Appendix J).

Theorem 6.19

When (a) alter's diversity multiplier is greater than zero, (b) alter's diversity multiplier is smaller than focal's multiplier, and (c) focal's technological diversity is greater than alter's technological diversity, then focal's performance is greater than alter's performance.

$\mathfrak{P}\ x,x',d,t,t'\ [D(x,d,t) \geq D(x',d,t') \wedge M(x,d,t) > M(x',d,t') \wedge M(x',d,t') > 0 \rightarrow$

$P(x,t) > P(x',t')]$

Proof for this theorem is provided by postulate 6.19 and 6.21 (see Appendix J).

Theorem 6.20

When (a) alter's diversity multiplier is smaller than zero, (b) alter's diversity multiplier is greater than focal's multiplier, and (c) focal's technological diversity is not smaller than alter's technological diversity, then focal's performance is smaller than alter's performance.

$\mathfrak{P}x,x',r,t,t'\ [D(x,d,t) \geq D(x',d,t') \wedge M(x,d,t) < M(x',d,t') \wedge M(x',d,t') < 0 \rightarrow P(x,t) < P(x',t')]$

Proof for this theorem is provided by postulate 6.20 and 6.22 (see Appendix J).

This concludes our diversity argument, which is graphically displayed in Figure 6.4. The existence of multiple technological systems with distinct growth rates naturally draws our attention to yet another dimension of the technological niche, namely technological opportunities.

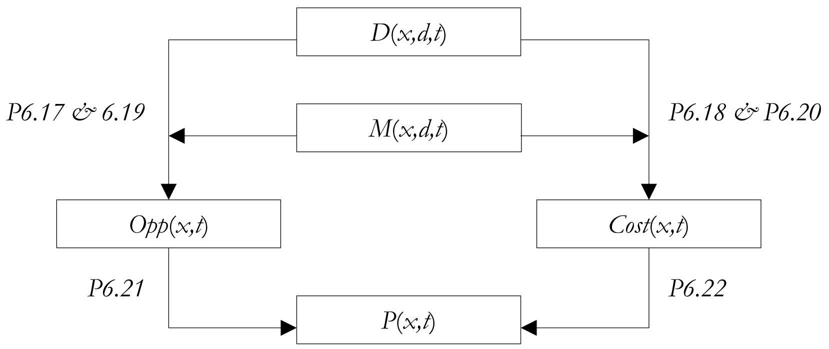

Figure 6.4 Argumentative structure diversity

6.6 Technological opportunities

We have already argued that, due to an organization's bounded rationality, its technological search processes are highly localized (Fleming, 2001; Nelson & Winter, 1982), and therefore highly path dependent (Podolny et al., 1996). Because technology is considered as one of the core features of the organization, this also connects to organizational ecology's structural inertia theory (Hannan & Freeman, 1984). Thus, organizations are highly dependent on the environment in which they are currently active and the opportunities that are provided in this environment. It logically follows that the organization's technological opportunities are a function of the opportunities within the technological systems in which it is currently active. We define this formally as follows.

Definition 6.14

The technological opportunities of an organization are defined as

$$TO(x,t) = \sum_{s}^{S} \tau_{xst} \cdot T(s,t)$$

where τ_{xst} refers to the share of patents that organization x has in technological system c at time t, and $T(s,t)$ to the opportunities in technological system s at time t.

Obviously, an increase in the organization's technological opportunity, ceteris paribus, results in higher performance improvements (Dosi, 1988). Now, we can formulate our next postulate.

Postulate 6.23

Increasing an organization's technological opportunities increases the organization's general opportunities.

$\mathfrak{N}\ x,x',r,t,t'\ [TO(x,t) \geq TO(x',t') \rightarrow Opp(x,t) > Opp(x',t')]$

Postulate 6.20 already relates the organization's opportunities to its performance. This means that we have all the necessary ingredients to develop the theorems that follow from this logic.

Theorem 6.21

If (a) an organization's share in a technological system remains equal, (b) the technological opportunities in that technological system increase, and (c) the remaining technological opportunities do not decrease, then the organization's performance increases.

$\mathfrak{P}\ x,s,t,t'\ [\tau_{xst} = \tau_{xst'} \wedge TO(s,t) > TO(s,t') \wedge \forall\ w\ [s \neq w\ \wedge \sum_{w}\tau_{xwt} \cdot TO(w,t) \geq \sum_{w}\tau_{xwt'} \cdot TO(w,t')]$
$\rightarrow P(x,t) > P(x,t')]$

Proof for this theorem is provided by definition 6.14 and postulates 6.21 and 6.23 (see Appendix J).

Theorem 6.22

If (a) focal's share of opportunities in a technological system is greater than alter's share, while (b) that technological system has a higher growth rate than all other systems, and (c) focal's remaining opportunities are not smaller than alter's remaining opportunities, then the performance of focal is greater than the performance of alter.

$\mathfrak{P}\ x,x',s,t,t'\ [\tau_{xst} > \tau_{x'st'}\ \wedge \forall\ w\ [TO(s,t) > TO(w,t')] \wedge \forall\ z\ [z \neq w\ \wedge \sum_{z}\tau_{xzt} \cdot TO(z,t) \geq \sum_{z}\tau_{xzt'} \cdot$
$TO(z,t')] \rightarrow P(x,t) > P(x',t')]$

Proof for this theorem is provided by definition 6.14 and postulates 6.21 and 6.23 (see Appendix J).

This concludes our technological opportunities argument, which is graphically displayed in Figure 6.5.

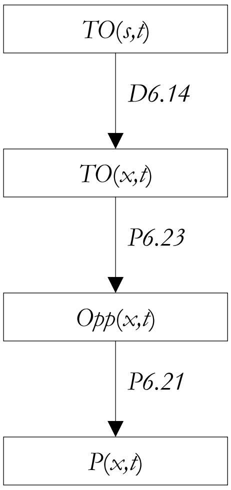

Figure 6.5 Argumentative structure technological opportunities

6.7 Organizational performance

In Chapter 5, we have already argued that organizational performance is a general construct that can be measured in various ways. This, as such, facilitates investigating the effects of crowding and status on multiple organizational outcomes. However, as we have completely left out the temporal dimension of organizational performance in our formalization, these arguments are of a rather static nature. In the current chapter, we have added time to this equation, which enables a more dynamic investigation. Obviously, different performance measures require different temporal structures. For example, consider the temporal dimension of an effect of the organization's technological niche on its rate of innovation (cf. Chapter 7) versus its mortality hazard. Clearly, organizational innovation is temporally much more proximate to our arguments than organizational mortality. This implies that an analysis with the organization's rate of innovation as the performance measure would require a shorter time span that an analysis with organizational mortality as the outcome construct-of-interest. To facilitate the testing of such diverse research questions, we define organizational performance as a matrix that consists of two dimensions, namely (1) performance characteristics and (2) time or duration. This creates a flexible, general model that allows for a systematic investigation of the characteristics of an organization's technological niche on different performance characteristics over time.

Definition 6.15

Organizational performance is defined as a two dimensional matrix

$$\Pi_{xt} = \begin{pmatrix} \pi_{11} & \cdots & \pi_{1t} \\ \vdots & \ddots & \vdots \\ \pi_{i1} & \cdots & \pi_{it} \end{pmatrix}$$

where x is an organization, and π_{it} is the score on performance characteristic i at time t

As noted above, numerous performance characteristics can be easily imagined, such as organizational innovation, profits, sales, growth, the ability to attract capital, employees or partners, and the ultimate performance measures, organizational survival.

6.8 Discussion and conclusion

In the current chapter, we have integrated some of our major findings regarding the growth and evolution of technology from Chapters 3 and 4 into our formalized theory fragments from Chapter 5. More specifically, we place organizations in a technological landscape composed of multiple technological systems in different stages of development. In all, we put forward numerous theorems that can be easily translated into hypotheses for empirical validation. In so doing, not only do we extend the theory of the organization-specific technological niche as such, but we also provide opportunities for further theory extension. In the current section, we like to reflect on five of these.

First, the effect of technological (non-)crowding on the organization's performance is conditional on the stage of development of the particular technology, and on the dyad-specific competition and legitimation coefficient of the crowding organizations. This suggests that the effect of crowding on organizational mortality can change due to (1) a change in the degree of crowding by either one of the crowding organizations (i.e., focal or alter), (2) convergence on a dominant design (i.e., the transition of a technological system from the seed to the growth stage development) and, finally, (3) through changing the competition or legitimation coefficient. While the second option is clearly the result of integrating the evolution of technology into the argument of technological crowding, the third option opens the door to include processes that alter the legitimation or competition coefficient (e.g., by engaging in a strategic alliance, by entering or exiting markets, or through market-partitioning processes). Obviously, this allows to include other organizational characteristics (e.g., the distinction between profit and non-profit organizations, size distinctions, industry membership, age, and so on and so forth) as well, to investigate processes that alter either one of these coefficients. The coefficients can thus be viewed as a function that is dependent upon the distance or similarity of the vectors of organizational characteristics of focal and alter.

Second, we have added non-crowding to represent the competitive processes between alternative design configurations in the seed stage of development, and to represent legitimation processes between organizations working on alternative parts of the dominant design configuration in the growth stage of development. These effects are mediated by the respective coefficients. The general effects of crowding and non-crowding in the different stages of technological development are displayed in Table 6.1. However, this logic is based on the assumption that in the growth stage of technological development no alternative design configurations exists, and that in the seed stage of development alternative design configurations do exist. Undeniably, this is a limiting assumption, but relaxing this assumption at this stage would make our model overly complex. It does, however, provide an interesting avenue for future research. In this context, fuzzy set theory (cf. Hannan et al., 2007) offers a valuable toolkit to determine the extent to which different design configurations can be identified, and to determine the extent of support for these design configurations by both individual and populations of organizations. In view of this, connecting the existence of alternative design configurations to the level of uncertainty within a technological domain is certainly an interesting avenue to explore.

Third, partly due to our focus on emerging technology, only two stages of technological development have been identified (i.e., seed and growth). Clearly, additional stages can be readily conceived, such as the maturity and decline stages of technological evolution. Extending our arguments from a two-stage theory to a four-stage theory is rather straightforward, as all elements are already present. It goes without saying that we are only referring to the logic part of such an extension, and not to the substantive arguments regarding the processes in the different stages. Regarding the substantive arguments, modeling the decline stage of technological development requires relating the stages of development of different systems to one another. That is, the decline stage only sets in when the focal technological system experiences competition from an alternative (more fit) technological system. Another extension would be to also consider the situation where the dominant design configuration is overthrown by an alternative design configuration from within, implying a revolutionary stage of the system (i.e., a revisit to the seed stage to redefine the dominant design configuration). These two alternative scenarios are displayed in Figure 6.6 below.

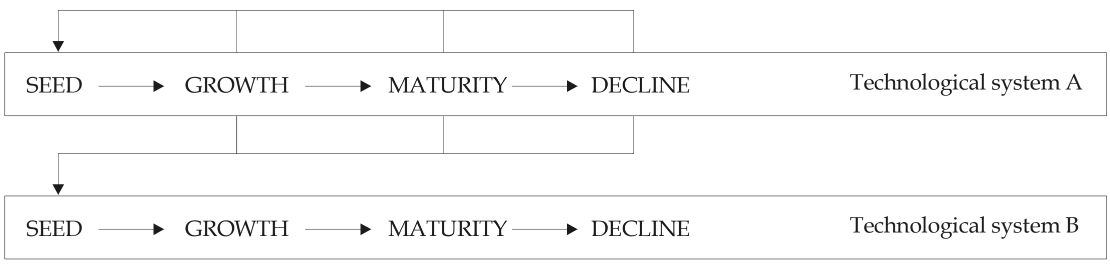

Figure 6.6 Alternative effects of system changes

This links nicely to our previous discussion about the existence of alternative design configurations in the growth stage of technological development. Moreover, allowing for a revolutionary stage in which the basic design configuration is redefined also connects rather well to the punctuated equilibrium framework as conceived by Gould and Eldredge (1972), which has already been applied to technology by Tushman and Anderson (1986). Even more ambitious is to relate the different stages of technological development at different levels of analysis, for example, by relating the evolution of technological components to the evolution of technological systems (or even technological landscapes, for that matter).

Fourth, by simultaneously considering the lineage of technology and multiple technological systems, we were able to define three dimensions of technological diversity (i.e., antecedent, focal, and descendant diversity). Viewing these dimensions over time (i.e., dynamically) allows for a process analysis of the organization's technological niche (i.e., the position of the organization in the technological landscape). This opens the door to a dynamic investigation of how organizations search and move through the technological landscape. Another avenue is to study how re-combinations (or novelty) enter the organization, by connecting these dimensions to the work done by Fleming (2001). Even though we have concentrated our attention on the diversity of technological lineage, other characteristics are also possible, some examples being variety (MacArthur, 1965), balance (Pielou, 1969), similarity (Tversky, 1977), and disparity (Solow & Polaski, 1994; Weitzman, 1992). Because we have chosen for a rather general formal model, it can be rather easily extended to include these dimensions. Eventually, after empirical evidence has narrowed down the possibilities and options, a more informed model might even be constructed that explains the processes of competition and legitimation even more accurately.

Fifth, by adding technological opportunities as a dimension to the theory of the technological niche, it becomes possible to decompose an organization's growth into an environmental part (i.e., external opportunities) and an organization-specific part (i.e., internal capabilities). In other words, this implies a distinction between the opportunities that are presented to the organization as a result of its position in the environment (i.e., being in the right place at the right time), and between the organization's ability to translate these opportunities into performance (i.e., being able to take advantage of the opportunities encountered). Consequently, technology might be the missing link in the debate between organizational adaptation and environmental selection perspectives.

Sixth, we have defined organizational performance as a two-dimensional matrix, consisting of performance characteristics and time duration. This specification allows us to insert different performance characteristics with different lag structures, effectively creating a flexible model to relate the dimension of an organization's (technological) niche to organizational performance. In so doing, we facilitate the investigation of the validity of our arguments and theorems using different performance characteristics and temporal structures. This, in turn, enables distinguishing between processes that are more distant (e.g., exploration) and more proximate (e.g., exploitation) in time, and analyzing the tradeoffs that might be involved in these processes. Important in this respect is a multidimensional operationalization of the concept of fit to determine the alignment of organizations along different dimensions of the multi-layered, multi-dimensional environment. With such a generalized econometric framework for the measurement of fit or alignment becoming available now (Parker and van Witteloostuijn, 2009), there is an opportunity for a significant advancement of research on the technological alignment of an organization in its environment. This new methodology uses a generalized model of (organizational) performance in combination with a new set of test statistics (based on the concept of Incremental Contribution) that unifies existing approaches to estimating fit, and moves beyond the current state-of-the-art by offering the opportunity to increase the estimation's explanatory power and limit the danger of obtaining biased estimates. In conjunction with the different dimensions of the technological niche, such an analysis would provide important insights in the process of technological and organizational change.

Chapter 7

An Empirical Test of the Extended Theory of the Technological Niche

7.1 Introduction

In the previous chapter, we have extended the theory of the organization-specific technological niche by integrating knowledge about the growth and evolution of technology. Through the use of formal logic, we have ensured that our extended arguments are logically sound and complete. However, this does not mean that the substantive part of our arguments is also valid. For this, empirical evidence is needed. After all, according to the scientific method, hypotheses need to be formulated and tested. Therefore, the aim of the current chapter is to translate several of our theorems from the previous chapter into hypotheses, to subsequently test them using sophisticated multivariate analysis. Our empirical setting is the biotechnology industry from 1980 until 2005. In doing so, we substantiate some of the theorems from the previous chapter. To be precise, we demonstrate that technological diversity also plays an intricate role in technological development at the organizational level of analysis, and that an organization's technological quality and technological opportunities also contribute significantly to an organization's rate of innovation (as measured by awarded patents). Nevertheless, we also encounter some anomalous findings, which provide an opportunity to further calibrate the theoretical arguments.

The contribution of this chapter is threefold. First of all, we validate part of our extension of the theory of the technological niche in the previous chapter, hereby providing support for the further integration of theories of technology and organization. Second, in so doing, we demonstrate the ease of translating theorems into hypotheses for empirical validation, which exemplifies the added value of using logical rigor in theory analysis and development. Third, by developing further insight in the process of technological growth and associated path dependence at the organizational level of analysis, we can close part of the chasm in the ongoing debate between organizational adaptation and environmental selection, and suggest that technology might be one of the important missing links in this debate.

The structure of this chapter is as follows. First, in Section 7.2, on the basis of selected theorems from the previous chapter, we will develop several hypotheses that relate the dimensions of the technological niche to organizational innovation. Next, Section 7.3 describes our empirical setting (i.e., biotechnology) and elaborates on the associated measures and methods used in our analysis. The results of our analysis are provided in Section 7.4. Finally, Section 7.5 discusses our results in the context of this dissertation and the wider academic debate.

7.2 The Technological Niche and Organizational Innovation

In the previous chapter, by integrating knowledge of the growth and evolution of technology, we have logically extended the theory of the organization-specific technological niche. In doing so, we have developed several theorems that presents the core of our knowledge in highly condensed, eloquent logical formulas. In the current chapter, as mentioned, we aim to find out whether some of these theorems hold their ground when subjected to a thorough empirical test. This implies that we will keep the theoretical discussion in this chapter to a minimum, and instead concentrate our attention on testing the previously developed theorems as much as possible. However, before we can effectively do so, we need to translate these theorems into specific hypotheses that can be empirically validated. In the current chapter, the performance measure of interest is organizational biotechnology innovation, as reflected in the number of granted patents. The reason for choosing this particular performance measure is threefold. First, this performance measure stands relatively close to the dimensions of the technological niche, which implies that the time lag between our dependent and independent variables can be kept to a minimum. This makes it possible to make optimal use of our data, as longer time lags reduce the number of observations that can be effectively used in the analysis. Second, because of the importance placed on patents within biotechnology (i.e., all landmark innovations have been patented), patent-based measures accurately reflect the outcome of organizational innovation processes. Third and finally, because of the importance placed on innovation and patents within biotechnology, there is a tight link between organizational innovation and the ultimate organizational performance measure, organizational survival.[24] That is, an organization's survival chances within a particular technological system – and its related downstream (product) markets – are intimately related to the organization's innovative capabilities within that same technological system. After all, in time, without the necessary technological competencies, the organization is bound to lose its position to better equipped and, therefore, more fit competitors. Now that we know the performance measure of interest, we continue with the formulation of our hypotheses.

[24] We have decided to focus on organizational innovativeness rather than survival because measuring organizational exit from biotechnology is anything but easy. Key is to decide on the duration of non-patenting that signals exit from biotechnology. We leave this issue for future research.

7.2.1 Crowding

First of all, according to our crowding argument, the effects of crowding and non-crowding are conditional upon the stage of development of the technological system. As we have argued in Chapter 4 of this dissertation, from a systemic point of view, biotechnology is not yet in a growth stage of technological development. This view is supported by Pisano (2006), who argues that biotechnology consists of several, distinct components that are still in development, rapidly evolving, and highly immature. So, even though biotechnology already displays systemic properties, many of its component technologies have only just been discovered and have yet to be integrated. Only after this integration is complete (i.e., after a dominant design configuration has been established), will growth become truly cumulative and can biotechnology be considered as being in the growth stage of development. Regarding the effect of crowding in the seed stage of technological development, due to the existence of multiple, competing design configurations, crowding increases the legitimation of the supported design configuration, and enhances its competitive potential vis-à-vis competing design configurations. It therefore strengthens the competitive position of the set of supporting organizations versus all other organizations in the population. According to Theorem 6.1, crowding contributes to the organization's performance by increasing the likelihood that the supported design configuration will become the dominant one. Accordingly, it also raises the chances of additional innovations by the organization in the technological system. This also implies that non-crowding increases the competitive potential of alternative design configurations, and thus decreases the organization's innovative potential (i.e., Theorem. 6.5). Our next pair of hypotheses thus becomes as follows.

Hypothesis 7.1: *The overlap of an organization's biotechnological niche is positively associated with its rate of biotechnology innovation.*

Hypothesis 7.2: *The non-overlap of an organization's biotechnological niche is negatively associated with its rate of biotechnology innovation.*

7.2.2 Status

Following our status argument, the relationship between, on the one hand, the organization's status and its rate of innovation, and, on the other hand, the organization's technological quality and its rate of innovation is mediated by the level of uncertainty within a technological system. However, due to the fact that technological development can never be characterized by complete uncertainty or uncertainty, both the organization's biotechnology status (i.e., Theorem 6.9) and biotechnology quality (i.e., Theorem 6.10) contribute positively to the organization's rate of innovation. This is represented by the following set of hypotheses.

Hypothesis 7.3: *An organization's biotechnology status is positively associated with its rate of biotechnology innovation.*

Hypothesis 7.4: *An organization's biotechnology quality is positively associated with its rate of biotechnology innovation.*

7.2.3 Global focal diversity

The general nature of our diversity argument causes the translation of these theorems into concrete hypotheses to be somewhat more involved. In the current chapter, because we are investigating the rate of innovation within a specific technological system – i.e., biotechnology – we can define the dimensions of technological diversity at two obvious levels of analysis. First, an organization's technological diversity can be defined at the level of a technological landscape, by taking into account the distribution of patents (i.e., for our measure of focal diversity) or patent citations (i.e., for our measures of antecedent and descendant diversity) among alternative technological systems. Second, focusing in on biotechnology, an organization's technological diversity can also be defined within this particular technological system, by considering the distribution of patents (i.e., for our measure of biotechnological diversity) or patent citations (i.e., for our measures of biotechnological antecedent and descendant diversity) among biotechnology's component technologies. Hence, in the current paper, we will define technological diversity at both levels of analysis. We start at the level of a technological landscape.

As argued in the previous chapter, focal diversity refers to the width of the organization's technological niche, increasing the organization's innovative potential by increasing flexibility and preventing path dependence. However, according to the principle of allocation, there is a tradeoff between niche width and strength of appeal, implying that flexibility comes at a price. As we are concerned with the innovative potential within one particular system (i.e., biotechnology), the flexibility to switch between alternative technological systems has no added value whatsoever. In other words, the width of the organization's technological niche within the landscape contributes little to developments within one particular system. So, from the perspective of a single technological system, there are only costs associated with focal diversity, as inter-system slack implies a reduction in resources that can be devoted to intra-system developments. Thus, we expect focal diversity to have a negative effect on the organization's rate of biotechnology innovation. We build upon Theorem 6.18 to construct our next hypothesis.

Hypothesis 7.5: *An organization's global focal diversity is negatively associated with its rate of biotechnology innovation.*

7.2.4 Global antecedent diversity

Antecedent diversity refers to the extent to which the organization's knowledge comes from different systems in the technological landscape (recall that the organization's technological antecedents are the knowledge on which the organization builds in constructing its focal technology). The more diverse the organization's knowledge base, the higher the organization's absorptive capacity. After all, an organization's absorptive capacity is a function of its prior related knowledge (Cohen & Levinthal, 1990; Van den Bosch et al., 1999; Zahra & George, 2002). And because the unknown (i.e., new knowledge) always has to be related to what is known (i.e., old knowledge), increasing what is known increases the capacity to absorb new knowledge. As such, it increases the organization's recombination potential or, in other words, its ability to put old things in new combinations and new things in old combinations (Weick, 1979), which elicits the sort of learning and problem solving that yields innovation (Simon, 1957). Hence, in accordance with Theorem 6.19, we expect a positive effect of antecedent diversity on the organization's rate of biotechnology innovation, and formulate the following hypothesis.

Hypothesis 7.6: *An organization's global antecedent diversity is positively associated with its rate of biotechnology innovation.*

7.2.5 Global descendant diversity

Descendant diversity refers to the extent to which the organization's technology is diffused throughout the technological landscape. Because a direct technological tie cannot be uniquely interpreted (Podolny et al., 1996), descendant diversity is a two-edged sword. On the one hand, it implies legitimation of the organization's technology. On the other hand, the presence of technological developments highly similar to the organization's developments increases the potential for competition. From this, we might formulate two alternative hypotheses. In line with Theorem 6.17, the effect of descendant diversity is expected to be positive. However, in accordance with Theorem 6.18, we expect descendant diversity to have a negative effect on the organization's rate of biotechnology innovation, due to the fact that status is argued to capture the positive effect. Our next pair of hypotheses becomes as follows.

Hypothesis 7.7: *An organization's global descendant diversity is positively associated with its rate of biotechnology innovation.*

Hypothesis 7.7alt: *An organization's global descendant diversity is negatively associated with its rate of biotechnology innovation.*

7.2.6 Biotechnology-specific focal diversity

Next, we consider the role of the different dimensions of diversity at the system level – i.e., biotechnology-specific diversity. Focal biotechnology diversity is indicative of the width of the organization's biotechnological niche. Even though our diversity argument from the previous chapter allows for both a positive and a negative effect, which would suggest two alternative hypotheses, we expect focal biotechnology diversity to contribute in a positive way to the organization's rate of biotechnology innovation for two reasons. First, biotechnology is in a seed stage of development, which implies that several or many alternative design configurations exist. Increasing focal biotechnology diversity increase the organization's support for alternative design configurations (i.e., the extent to which the organization is actually part of the alternative design configurations), hereby providing flexibility and preventing path dependence (i.e., supporting technological dead ends) in a highly uncertainty environment. Second, focal (landscape) diversity already captures the negative effects of fragmentation and the cost of carrying unrelated slack. The slack that is represented by focal biotechnology diversity is highly related to biotechnology developments. Hence, we build upon Theorem 6.19 in constructing our next hypothesis.

Hypothesis 7.8: *An organization's biotechnology-specific focal diversity is positively associated with its rate of biotechnology innovation.*

7.2.7 Biotechnology-specific antecedent diversity

Obviously, antecedent diversity can also be defined at the level of a specific technological system. As such, it refers to the extent to which an organization's system specific knowledge is distributed among the system's components. Thus, in our case, it refers to the extent to which the organization's biotechnological knowledge is distributed among biotechnology's component technologies. In analogy to global antecedent diversity, biotechnology-specific antecedent diversity also has a positive effect on the organization's rate of biotechnology innovation. After all, an organization's absorptive capacity is largely a function of its prior related knowledge, and biotechnology-specific knowledge is obviously highly related to any development within biotechnology. Furthermore, increasing knowledge about biotechnology's component technologies increases the organization's knowledge about any alternative design configurations of these components, which increases the flexibility of the organization. Hence, we expect that biotechnological antecedent diversity is positively related to the organization's rate of biotechnology innovation. On the basis of Theorem 6.19, we thus formulate the following hypothesis.

***Hypothesis 7.9**: An organization's biotechnology-specific antecedent diversity is positively associated with its rate of biotechnology innovation.*

7.2.8 Biotechnology-specific descendant diversity

In a similar vein, descendant diversity can also be defined at the level of a specific technological system, and, as such, refers to the extent to which the organization's technology is diffused among the system's component technologies. Again, this type of descendent diversity is a two-edged sword: the legitimative effect of a direct technological tie suggests a positive relationship, and the competitive effect a negative one. The positive effect is in line with Theorem 6.17, and the negative impact with Theorem 6.18. We formulate our next pair of hypotheses accordingly.

***Hypothesis 7.10**: An organization's biotechnology-specific descendant diversity is positively associated with its rate of biotechnology innovation.*

***Hypothesis 7.10alt**: An organization's biotechnology-specific descendant diversity is negatively associated with its rate of biotechnology innovation.*

7.2.9 Biotechnological opportunities

Due to bounded rationality and local search, organizations are essentially bound to the (local) environment in which they are currently active. Therefore, in the previous chapter, we have argued that an organization's technological opportunities are a function of the technological opportunities in the technological system(s) in which the organization is active. Despite the fact that the organization's biotechnology-specific opportunities are clearly correlated with its global technological opportunities, it obviously makes more sense to consider the technological opportunities specific to the technological system under investigation. This also connects to our finding that biotechnology's component technologies provide distinct sets of opportunities in Chapters 3 and 4. Therefore, in concordance with Theorem 6.21, we expect that the organization's biotechnological opportunities are positive related to its rate of biotechnology innovation. Our next hypothesis thus becomes as follows.

***Hypothesis 7.11**: An organization's biotechnological opportunities are positively associated with its rate of biotechnology innovation.*

7.3 Data and methodology

Because patent data are the most direct and objective measure of innovation (Griliches, 1981; Thoma & Torrisi, 2007), patent data are used extensively in innovation and technology studies (cf. Fleming, 2001; Nooteboom, Vanhaverbeke, Duysters, Gilsing, &

van den Oord, 2007; cf. Podolny et al., 1996; Verspagen, 2005). Due to the importance placed on patents within biotechnology, all landmark innovations have been patented. As a result, patents form a reliable indicator of technological developments within biotechnology (Orsenigo et al., 2001; Powell et al., 1996). Thus, it should come as no surprise that we, again, heavily rely on patent data to test our hypotheses. More specifically, because previous research illustrates that the US patent system offers the most complete dataset for technology analysis (Podolny et al., 1996), we also rely on patent data from the United States Patent and Trademark Office (USPTO) in our analysis.

Our sample consists of all organizations that have ten or more biotechnology patents (represented by USPTO classes 435 and 800) as of January 2006.[25] The reason for this approach is threefold. First, because we are using yearly observations in our analysis, we keep the number of zeros in our analysis within an acceptable range. Because our period of observation is from 1980 to 2005 (i.e., 26 years), including all organizations with less than 10 patents in biotechnology would result in a great deal of zero values for our dependent variable. Second, this increases the likelihood that our substantive measures can be meaningfully constructed. Because many of our substantive variables are based on patent information, we need sufficient information to calculate these variables in such a way that they distinguish between organizations and over time. Moreover, a lack of variance in our measures could also result in problems of multicollinearity. Third and finally, this effectively leaves out all organizations that have an 'accidental' stake in biotechnology, and hereby focuses our attention on organizations with a true interest in biotechnology developments.

To construct our control variables, we have linked the USPTO data with numerous financial databases. These databases are, amongst others, Worldscope 1997, Compustat Global 2005, Compustat North America 2005, Amadeus editions 1996 and 2007, and Bioscan 2007. To delineate the ownership structure for aggregation purposes, we have used the Amadeus editions of 1996 and 2007, Thomson's Mergers and Acquisitions data (formerly known as SDC platinum) 2006, Bioscan 2007, and Bioworld 2007. Because no unique identifier exists across these databases (i.e., existing ID's such as SEDOL and CUSIP are not used consistently in the individual databases), the linking of these databases has been a colossal task (which implies a fourth reason for sample restriction). In each database, organizations are named slightly (or even completely) different due to several reasons, some of which are: (1) the complex legal structures of organizations (with many subsidiaries and holding companies), (2) spelling variations and errors, (3) additions (e.g., of legal forms, such as inc or nv), (4) acronyms (e.g., SRI, which stands for Stanford Research Institute), (5) abbreviations (e.g., inc. for incorporated) and (6) special characters (e.g., ß and ü). As a result, the matching of the

[25] This implies that our sample is biased. This should be kept in mind whilst interpreting the findings.

organizations in different databases was done via a rather complex algorithm that involves numerous manual and automated steps. Basically, because a unique identifier does not exist, one has to be created in each database in such a way that it is similar in the individual databases. However, because there is no guarantee that the organizations represented by similar identifiers in different databases are indeed one and the same, visual inspection was necessary to make the final decision. In all, this has proven to be a rather complex and iterative process, as outcomes of intermediate steps revealed unforeseen anomalies that required redesigning and fine-tuning of our algorithm, the subject which deserves a study of its own.

7.3.1 Measures

Biotechnology patents, our dependent variable, is a count of the number of issued (i.e., awarded, so excluding rejected) patents. Our data constitute a cross-sectional time-series, as we have repeated observations for the same organizations. This is an unbalanced panel, though, as organizations enter and exit during our period of observation.

Biotechnology crowding measures the extent to which an organization's antecedents from its biotechnology patents are crowded by other organizations (i.e., the extent to which these other organizations also cite these antecedents). This implies

$$(7.1) \qquad BC_{xt} = \sum_{y=1,\, y\neq x}^{y=Y} \frac{\left|A_{xbt} \cap A_{yt}\right|}{\left|A_{xbt}\right|}$$

where A_{xbt} refers to organization x's antecedents from its biotechnology patents at time t, and A_{yt} to organizations y's antecedents at time t', and Y to the set of all organizations in the population. Moreover, ∩ denotes the intersection of two sets, and |.| symbolizes the cardinality of a set.

Biotechnology non-crowding measures the extent to which an organization's antecedents from its biotechnology patents are non-crowded by other organizations. This means

$$(7.2) \qquad BNC_{xt} = \sum_{y=1,\, y\neq x}^{y=Y} \frac{\left|A_{xbt} \cup A_{yt'}\right| \setminus \left|A_{xbt} \cap A_{yt'}\right|}{\left|A_{xbt}\right|}$$

where A_{xbt} refers to organization x's antecedents from biotechnology at time t, A_{yt} to organizations y's antecedents at time t', and Y to the set of all organizations in the population, ∩ denotes the intersection of two sets. Moreover, ∪ denotes the union of two sets, \ set subtraction, and |.| the cardinality of a set.

Our measure of Biotechnology status is constructed using patent citations, as these provide a fair proxy of the perceived importance in a technological community (Hall, Jaffe, & Trajtenberg, 2005; Trajtenberg, 1990). This implies

(7.3) $$BS_{xt} = \frac{DA_{xt}}{\sum_{y=1}^{y=Y} DA_{yt}}$$

where DA_{xt} refers to the acts of deference (i.e., patent citations) that organization x receives from biotechnology at time t, DA_{yt} to acts of deference that organization y receives from biotechnology at time t, Y to all organizations in the population, and t to the five years prior to our the measurement date of dependent variable.

Next, Biotechnology quality represents the share of biotechnology that is owned by the organization. This is

(7.4) $$BQ_{xt} = \frac{T_{xbt}}{\sum_{y=1}^{y=Y} T_{ybt}}$$

where T_{xbt} refers to the share of technology in biotechnology that is owned by organization x at time t, T_{ybt} to the share of technology that is owned by organization y in biotechnology at time t, Y to all organizations in the population, and t to the five years prior to the date of measurement of our dependent variable.

Biotechnology opportunities involve the technological opportunities that an organization encounters within biotechnology due to its current position within biotechnology's component technology and their respective growth rates. This means

(7.5) $$BO_{xt} = \sum_{c=1, c\in B}^{c=C} \delta_{xtc} \zeta_{ct}$$

where δ_{xtc} refers to the share of patents that organization x has in technological component c at time t, ζ_{ct} to the growth rate of component c at time t, C to the set of all components within B (i.e., biotechnology), and t to the five years prior to the date of measurement of our dependent variable.

Antecedent diversity measures the extent to which the organization's knowledge originates from different technological systems, which implies

(7.6) $$AD_{xt} = \sum_{s=1}^{s=S} \theta_{xst} \ln(1/\theta_{xst})$$

where θ_{xst} is the share of technological antecedents of organization x at time t that come from technological system s, and S refers to the set of all technological systems.

Focal diversity refers to the extent to which the organization's technological developments take place in different technological systems, which is

(7.7) $$FD_{xt} = \sum_{s=1}^{s=S} \tau_{xst} \ln(1/\tau_{xst})$$

where τ_{xst} refers to the share of focal technology from organization x that comes from technological system s at time t, and S to the set of all technological systems.

Descendant diversity is a measure of the extent to which the organization's technology has diffused throughout the technological landscape. Thus,

$$(7.8) \quad D_{xdt} = \sum_{s=1}^{s=S} \upsilon_{xst} \ln(1/\upsilon_{xst})$$

where υ_{xst} is the share of technological descendants of organization x at time t that come from technological system s, and S refers to the set of all technological systems.

Bio-antecedent diversity is the extent to which the organization's biotechnological knowledge originates from biotechnology's components.

$$(7.9) \quad BAD_{xt} = \sum_{c=1, c\in B}^{c=C} \varphi_{xct} \ln(1/\varphi_{xct})$$

where φ_{xct} is the share of technological antecedents of organization x at time t that come from technological component c, and C refers to the set of all technological components from biotechnology or B.

Likewise, Bio-focal diversity is indicative of the extent to which the organization's developments within biotechnology take place in different components. Hence,

$$(7.10) \quad BFD_{xt} = \sum_{c=1, c\in B}^{c=C} \omega_{xct} \ln(1/\omega_{xct})$$

where ω_{xct} is the share of patents of organization x at time t that come from technological component c, and C refers to the set of all technological components from biotechnology (B).

Bio-descendant diversity refers to the extent to which the organization's technology is diffused among biotechnology's components. So,

$$(7.11) \quad BDD_{xt} = \sum_{c=1, c\in B}^{c=C} \eta_{xct} \ln(1/\eta_{xct})$$

where η_{xct} is the share of technological descendants of organization x at time t that come from technological component c, and C refers to the set of all technological components from biotechnology (B).

We include a number of control variables. First, we have the number of Previous entries to control for favorable conditions within the environment that may encourage entry (Delacroix & Carroll, 1983; Hannan et al., 1995). Essentially, this controls for some of the serial correlation that might remain in the data. Additionally, we add the total number of biotechnology patents, Biotechnology density, to account for the experience that the organization has in applying for patents in biotechnology. Furthermore, we also include the total number of patents in our measure of Global density, to control for the experience that the organization has with the general process of applying for patents. To avoid double counting, we exclude the number of biotechnology patents from this measure. Next, Biotechnology focus refers to the extent to which the organization is focused on biotechnology, represented by the share of biotechnology patent in the organization's portfolio. This implies

$$(7.12) \quad BF_{xt} = \frac{BP_{xt}}{P_{xt}}$$

where BP_{xt} refers to the number of patents that organization x has in biotechnology at time t, P_{xt} to the total number of patents of organization x at time t, and t to the five years prior to the date of measurement of our dependent variable.

Organizational age is measured in years. We have taken the natural log of Employees in thousands, the natural log of R&D expenditures in trillions of US dollars, the natural log of Revenues in billion of US dollars, and the natural log of Assets in billions of US dollars as measures of organizational features. Finally, we also include Year dummies to control for any year-specific effects. In Table 7.1, we provide descriptive statistics. The correlation matrix is presented in Table 7.2.

Table 7.1 Summary statistics

Variable	n	mean	S.D.	min	max	25th %	50th %	75th %
Biotechnology patents	4,896	9.21	15.37	0.00	212.00	1.00	3.00	10.00
Biotechnology crowding (thousands)	4,896	0.03	0.08	0.00	3.06	0.01	0.02	0.04
Biotechnology non-crowding (millions)	4,896	0.00	0.01	0.00	0.09	0.00	0.00	0.00
Biotechnology status	4,896	0.00	0.00	0.00	0.03	0.00	0.00	0.00
Biotechnology quality	4,896	0.00	0.00	0.00	0.03	0.00	0.00	0.00
Biotechnology opportunities	4,896	0.10	0.04	0.00	0.38	0.08	0.10	0.12
Global antecedent diversity	4,896	2.60	1.02	0.00	4.87	1.93	2.44	3.04
Global focal diversity	4,896	2.26	1.09	0.00	4.73	1.50	2.05	2.65
Global descendant diversity	4,896	2.64	1.02	0.00	4.89	1.89	2.52	3.23
Bio-antecedent diversity	4,896	1.39	0.49	0.00	2.49	1.07	1.46	1.75
Bio-focal diversity	4,896	1.20	0.59	0.00	2.32	0.80	1.26	1.69
Bio-descendant diversity	4,896	1.43	0.49	0.00	2.59	1.11	1.51	1.79
Previous entries	4,896	9.61	15.37	0.00	212.00	1.00	4.00	11.00
Biotechnology focus	4,896	0.14	0.20	0.00	1.00	0.01	0.05	0.16
Biotechnology density (thousands)	4,896	0.13	0.17	0.00	1.30	0.02	0.06	0.17
Global density (millions)	4,896	0.01	0.01	0.00	0.05	0.00	0.00	0.01
Age (thousands)	4,896	0.11	0.08	0.00	0.34	0.06	0.10	0.14
Employees (thousands)	4,896	0.05	0.07	0.00	0.34	0.00	0.02	0.06
R&D expenditures (trillion $)	4,896	0.00	0.00	0.00	0.07	0.00	0.00	0.00
Revenues (trillion $)	4,896	0.02	0.04	0.00	0.53	0.00	0.01	0.02
Assets (billion $)	4,896	0.02	0.07	0.00	0.65	0.00	0.00	0.01

Legend: n = number of observations; S.D. = standard deviation; min = minimum value; max = maximum value; 25th = 25th percentile; 50th = 50th percentile; 75th = 75th percentile.

Table 7.2 Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1 Biotechnology patents	1.00																				
2 Biotechnology crowding (thousands)	-0.06	1.00																			
3 Biotechnology non-crowding (millions)	-0.17	0.40	1.00																		
4 Biotechnology status	0.46	0.01	-0.24	1.00																	
5 Biotechnology quality	0.56	-0.10	-0.26	0.71	1.00																
6 Biotechnology opportunities	0.26	-0.03	0.15	-0.06	-0.03	1.00															
7 Global antecedent diversity	0.12	-0.02	-0.16	0.39	0.28	-0.10	1.00														
8 Global focal diversity	0.10	-0.03	-0.15	0.38	0.27	-0.11	0.97	1.00													
9 Global descendant diversity	0.10	0.01	-0.10	0.35	0.24	-0.07	0.93	0.94	1.00												
10 Bio-antecedent diversity	0.29	-0.11	-0.32	0.28	0.29	0.08	0.12	0.14	0.14	1.00											
11 Bio-focal diversity	0.39	-0.11	-0.34	0.38	0.42	0.11	0.12	0.11	0.12	0.71	1.00										
12 Bio-descendant diversity	0.23	0.00	-0.14	0.24	0.28	0.05	0.10	0.11	0.16	0.60	0.61	1.00									
13 Previous entries	0.77	-0.04	-0.18	0.47	0.63	0.29	0.11	0.09	0.10	0.32	0.42	0.25	1.00								
14 Biotechnology focus	0.00	0.02	0.03	-0.23	-0.12	0.19	-0.54	-0.55	-0.55	-0.12	-0.10	-0.30	0.03	1.00							
15 Biotechnology density (thousands)	0.53	0.07	-0.20	0.60	0.63	0.09	0.22	0.19	0.23	0.42	0.53	0.39	0.67	-0.12	1.00						
16 Global density (millions)	0.26	0.06	-0.15	0.54	0.36	-0.05	0.67	0.69	0.67	0.26	0.30	0.25	0.28	-0.36	0.55	1.00					
17 Age (thousands)	0.32	-0.04	-0.21	0.54	0.55	-0.13	0.30	0.29	0.30	0.27	0.41	0.38	0.33	-0.46	0.52	0.43	1.00				
18 Employees (thousands)	0.18	0.12	-0.10	0.22	0.07	0.08	0.40	0.40	0.42	0.23	0.29	0.22	0.19	-0.28	0.38	0.61	0.31	1.00			
19 R&D expenditures (trillion $)	0.15	0.07	-0.11	0.17	0.14	0.01	0.22	0.21	0.22	0.19	0.26	0.17	0.18	-0.20	0.31	0.35	0.27	0.40	1.00		
20 Revenues (trillion $)	0.15	0.07	-0.09	0.36	0.23	-0.04	0.59	0.60	0.58	0.18	0.25	0.20	0.17	-0.29	0.34	0.73	0.37	0.52	0.38	1.00	
21 Assets (billion $)	0.04	0.12	-0.03	0.26	0.03	-0.01	0.37	0.37	0.36	0.12	0.17	0.06	0.07	-0.14	0.33	0.63	0.23	0.64	0.25	0.50	1.00

As can be seen in Table 7.2, the high correlations within (and not between) our sets of global and biotechnology-specific diversity measures, among some of our control variables (i.e., employees, revenues, assets, and R&D expenditures), and among status, quality, age, biotechnology density, and global density warrants us to proceed with some caution to ensure that our estimates do not suffer from multicollinearity.

7.4 Estimation

As mentioned before, our dependent variable is a yearly count of the number of biotechnology patents granted to our focal organizations. The baseline for modeling count data is the Poisson distribution, and adding covariates gives the Poisson regression model. Due to the mean-variance equality restriction of the Poisson distribution, after regression, the variance has to be roughly equal to the mean of the dependent variable. A useful rule of thumb is that the variance cannot be more than roughly twice the mean, since social science data never explain more than 50 per cent of the variance (Cameron & Trivedi, 1998). In the case that the variance is larger, the dependent variable suffers from what is called overdispersion, due to unobserved heterogeneity. This implies that the distribution of this variable has a fat tail, with many extreme observations that significantly increase the variance. As can readily be observed from Table 7.1, the mean of our measure of Biotechnology patents is 9.121, while its variance is greater than 236 (i.e., 15.37^2). So, our dependent variable clearly suffers from overdispersion. Therefore, the Poisson regression model is not appropriate for our purposes, and we turn to the negative binomial regression model instead. The negative binomial regression model explicitly models overdispersion by adding a dispersion parameter to the Poisson regression model. Because our data constitute a cross-sectional time-series or panel structure, we need to use the panel version of the negative binomial model, which can be specified as follows (Cameron & Trivedi, 1986).

$$\text{(7.13)} \quad \Pr(Y_{it} = y_{it} \mid x_{it}, \delta_i) = \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)} \left(\frac{1}{1+\delta_i}\right)^{\lambda_{it}} \left(\frac{\delta_i}{1+\delta_i}\right)^{y_{it}}$$

with

$$\text{(7.14)} \quad \lambda_{it} = \exp(x_{it}\beta + \mathit{offset}_{it})$$

A negative binomial panel model comes in two basic flavors, namely a random effects and a fixed effects model. The random effects specification assumes that the dispersion parameter is drawn randomly from a certain distribution, usually a Gamma distribution, effectively creating a Beta distribution with parameters *r* and *s*. This enables the random effects specification to effectively use both the within and the between-variance of the panels (i.e., organizations in our case). Therefore, we have a slight preference for this model. However, the restriction of the random effects model is that the individual random effects are independent from the model's regressors (i.e., an assumption of orthogonality of the random effects and the regressors). To determine whether this is indeed the case, Hausman's (1978) specification test can be used, which is distributed as χ^2 and can computed

(7.15) $$H = (\beta_c - \beta_e)'(V_c - V_e)^{-1}(\beta_c - \beta_e)$$

where β_c is the coefficient vector from the consistent estimator, β_e the coefficient vector from the efficient estimator, V_c the covariance matrix of the consistent estimator, and V_e the covariance matrix of the efficient estimator. The degrees of freedom for this test statistic follow from the matrix rank of the variance of the difference between the coefficients of the two estimators.

As the name already indicates, the fixed effects specification adds a fixed effect for each panel. Consequently, it is also referred to as a within-variance model, as the individual fixed effect effectively removes all variance between panels, and provides the consistent estimator for the specification test in Equation (7.15) (Hausman, 1978). However, the conditional – conditional because the fixed effects are conditioned out of the likelihood equation – fixed effects negative binomial model as conceived by Hausman, Hall, and Griliches (1984) is not a true fixed effects specification (Allison & Waterman, 2002; Guimarães, 2008). The reason is that the model is based on a regression decomposition of the overdispersion parameter, rather than the usual regression decomposition of the mean (Allison & Waterman, 2002). As a result, the model only removes individual fixed effects equal to the logarithm of the overdispersion parameter (Guimarães, 2008). Because this condition is rather restrictive, the conditional fixed effects specification does not control for all stable covariates, and is therefore not a true fixed effects model. This implies that there is no guarantee that the conditional fixed effects negative binomial is completely free from serial correlation. Hence, the conditional fixed effects model does not provide for the consistent estimator required for Hausman's (1978) specification test in Equation (7.15). Common software packages, such as Stata and Limdep, have implemented the conditional fixed effects negative binomial specification of Hausman, Hall, and Griliches (1984). This becomes evident when you are allowed to include time-invariant covariates in the analysis, something which is usually not possible with conditional fixed effects models, as they effectively filter out all between-panel variance.

According to Allison and Waterman (2002), a good alternative is to specify a conventional non-panel negative binomial model (i.e., NB2 in Cameron & Trivedi, 1998), and manually add dummy variables to control for the fixed effects. Because the individual fixed effects are not conditioned out of the likelihood function, but are explicitly modeled using dummy variables, we will subsequently refer to this specification as the unconditional fixed effects negative binomial model. Nevertheless, the unconditional fixed effects negative binomial model does not come without problems either. To be precise, in the case that T (i.e., the number of time periods – or, in our case, years) is fixed and N (i.e., the number of panels – or, in our case, organizations) goes to infinity, the number of parameters in a fixed effects specification increases with the number of cross-sectional observations, which results in biased coefficient estimates (Hsiao, 2003), as it renders the maximum likelihood estimator inconsistent (Greene, 2003). This is referred to as the incidental parameters problem.[26] However, despite an irrefutable theoretical inconsistency (Greene, 2001), Allison and Waterman (2002) find no evidence for any incidental parameter bias for the unconditional fixed effects model in a simulation study of 100 panels and two time periods (i.e., $N = 100$ and $T = 2$). Our sample contains roughly 440 organizations and, on average, approximately 10 years (i.e., $N = 440$ and $T = 10$). Due to the relative likeness to Allison and Waterman's sample, we do not expect our data to suffer from the incidental parameters problem.[27] Nonetheless, just to be on the safe side, we estimate both the conditional and unconditional fixed effects specification, as well as the random effects specification. Even though the random effects and the conditional fixed effects specification might suffer from serial correlation, and the unconditional fixed effects might suffer from incidental parameter bias, when estimating all specifications, consistency of estimates across different specifications increases confidence in our findings. After all, according to Hausman, Hall, and Griliches (1984), model choice is always a choice between some "disturbance" in the equation.

7.5 Results

We have used Stata 8.0 SE to estimate our models. To be precise, our random effects negative binomial dispersion models (RE NB) were estimated with the 'xtnbreg, re' command and the conditional fixed effects models (CFE NB) with the 'xtnbreg, fe' command. To estimate our unconditional fixed effects models (UFE NB), we have manually added panel dummies and used the 'nbreg' command. Our estimates are provided in Table 7.4, and the different specifications provide, with a few exceptions, highly consistent estimates for most our variables.[28] Because we are currently unaware of how the different specifications impact on our analysis, we will not expand in great detail on the differences between alternative model specifications. Instead, we will concentrate our attention on reporting the consistent findings across alternative specifications. To make sure that our estimates are not the result of multicollinearity, we have also estimated numerous alternative models (not reported here, for the sake of brevity:

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[26] Because conditional models condition out the fixed effects, these models do not suffer from the incidental parameters problem (Allison and Waterman, 2002).

[27] Actually, our sample is somewhat better than Allison and Waterman's (2002) because we have a larger T value (i.e., 10 instead of 2) and a lower N/T ratio (i.e., 44 instead of 50).

[28] Due to space restrictions, in the current section, we only report the coefficient values and significance levels, but exclude the standard errors, which are reported in Tables 1 and 2 in Appendix K.

available upon request), in which we systematically exclude all highly correlating variables. Stability of coefficients and significance levels across these different models further strengthen our confidence that the results of our analysis are not caused by multicollinearity.

Model 1 estimates our restricted (i.e., including all control variables) random effects negative binomial model, and Models 2 and 3 estimate the restricted conditional and unconditional fixed effects, respectively. Model 4 estimates our unrestricted (i.e., without financial controls) random effects negative binomial model, while Model 5 and 6 estimate the restricted conditional and unconditional fixed effects specification, respectively. As most of our coefficient estimates are highly consistent across alternative specifications, we are confident that our findings are not coincidental or spurious. In all, we end up with approximately 441 organizations and 4,896 observations for our restricted model, and approximately 921 organizations and 14,186 observations for our unrestricted model.[29] This implies an average of 11.1 and 15.4 observations per organization for our restricted and unrestricted models, respectively. Even though our data are highly skewed towards North American organizations (see Table 7.3 below), additional analyses (not reported here, for the sake of brevity: available upon request) indicate that both the coefficients and significance levels are highly similar when excluding North American organizations from our analysis.

We use Model 2 to report our findings because this model has the lowest log-likelihood value. Because all models suffer from some disturbance that can potentially result in biased estimates, our choice is merely one of convenience and does not imply that this model is better in any way.

Table 7.3 Number of organizations and observations from different regions used in our analyses

Region	Organizations Restricted	Observations Restricted	Organizations Unrestricted	Observations Unrestricted
Asia	64	521	124	2,093
Europe	100	1,156	164	2,921
Oceania	1	5	9	102
North America	276	3,214	624	9,070
Total	**441**	**4,896**	**921**	**14,186**

Our estimates do not support Hypothesis 7.1, which argues that system crowding has a positive effect on the organization's rate of innovation due to existence of alternative design configurations. Quite the opposite, we find a consistent and highly significant negative effect. Increasing the value of crowding from its 1st quartile to its

[29] The number of organizations and observations for our conditional fixed effects models is slightly lower due to exclusion of single observations and zero group outcomes.

median value decreases the rate of innovation with 7 per cent, while further increasing crowding to the 3rd quartile decreases the rate of innovation with another 13 per cent.

In contrast, Hypothesis 7.2 is confirmed by our estimates, implying that non-crowding is negatively related to organizational innovation in biotechnology due to competition from alternative design configurations. Increasing non-crowding from its 1st to its 2nd quartile decreases the rate of innovation with 1 per cent, and further increasing non-crowding to its 3rd quartile decreases the rate of entry with another 3 per cent.

Hypothesis 7.3 states that, due to the high uncertainty level of biotechnology developments, biotechnology status has a positive effect on the rate of innovation. This hypothesis is rejected by our estimates. Status has a highly significant negative effect in all fixed effects specifications, while it has an insignificant negative effect in both random effects specifications.

Next, according to Hypothesis 7.4, quality has a positive effect on the organization's innovative capabilities. This hypothesis is fully confirmed by our estimates. Increasing the value of biotechnology quality from its first to its second quartile increases the rate of innovation with 6 per cent, and increasing its value from the median to the third quartile increases the multiplier with an additional 18 per cent.

Hypothesis 7.5 argues that focal diversity has a negative effect on the rate of innovation due to the cost of carrying "between-system slack" that has no value within one particular system – i.e., biotechnology. Even though the coefficient is consistently negative in all our restricted models, it is consistently positive in our unrestricted models. Hence, we refrain from drawing any conclusions regarding the effect of focal diversity.

Following the logic of Hypothesis 7.6, antecedent diversity increases the organization's absorptive capacity, being positively associated with the rate of biotechnology innovation. Our estimates do support this hypothesis and reveal a rather strong effect, indicating the importance of this measure. Increasing the value of antecedent diversity with one standard deviation increases the rate of innovation with as much as 102 per cent.

Hypothesis 7.7 claims that the legitimation effect is positive, whereas Hypothesis 7.7alt argues that the competitive potential of descendant diversity is negatively related to biotechnology innovation. Neither hypothesis can be confirmed by our estimates. The coefficient is significant in all but one of our models. Moreover, the sign of the coefficient switches, indicating an ambiguity that prevents us from drawing any conclusions regarding the effect of descendant diversity.

Our findings are consistent with Hypothesis 7.8, which asserts that focal biotechnology diversity is positively associated with the rate of biotechnology innovation by providing flexibility. Increasing the value of bio-focal diversity with one standard deviation increases the organization's rate of biotechnology innovation with 13 per cent.

Table 7.4 Restricted negative binomial panel regression estimates

	1	2	3	4	5	6
	RE NB R	**CFE NB R**	**UFE NB R**	**RE NB U**	**CFE NB U**	**UFE NB U**
Biotechnology crowding (thousands)	-5.931***	-7.024***	-9.096***	-6.020***	-9.878***	-9.25***
Biotechnology non-crowding (millions)	-34.151***	-19.342***	-16.379***	-29.503***	-30.475***	-11.275***
Biotechnology status	-4.424	-18.165***	-19.180**	-1.439	-10.469**	-13.958**
Biotechnology quality	67.959***	73.983***	72.934***	84.723***	90.424***	99.192***
Biotechnology opportunities	2.786***	2.577***	1.595**	3.191***	2.862***	4.968***
Global antecedent diversity	0.609***	0.686***	0.727***	0.261***	0.187***	0.293***
Global focal diversity	-0.121	-0.210**	-0.507***	0.121**	0.044	0.178***
Global descendant diversity	-0.173***	-0.098	0.250***	-0.139***	-0.244***	-0.078**
Bio-antecedent diversity	0.01	0.014	-0.131**	-0.030	-0.219***	-0.132***
Bio-focal diversity	0.350***	0.203***	0.242***	0.322***	0.263***	0.226***
Bio-descendant diversity	-0.125***	-0.185***	-0.297***	-0.071***	-0.240***	-0.254***
Previous entries	0.003***	0.003***	0.008***	0.007***	0.008***	0.016***
Biotechnology focus	0.870***	0.178	-0.241	0.197**	-0.796***	0.312***
Biotechnology density (thousands)	0.772***	0.614***	0.814***	-0.131	-0.886***	-1.331***
Global density (millions)	-2.895	-3.109	-9.270*	3.517	8.414***	2.202
Age (thousands)	3.033***					
LN(Employees (thousands))	0.065***	0.043*	0.095***			
LN(R&D expenditures (trillion $))	0.183	0.103	0.225			
LN(Revenues (trillion $))	-0.168***	-0.079**	-0.227***			
LN(Assets (billion $))	0.054*	0.086***	0.072**			
Constant	-0.68			-2.429***		
Alpha			0.168***			0.239***
r, of Beta(r,s)	3.292***			3.228***		
s, of Beta(r,s)	4.692***			3.421***		
Observations	4,896	4,838	4,896	14,186	14,133	14,186
Number of organizations	441	417	441	921	907	921
Degrees of freedom	43	42	483	38	38	959
Log likelihood	-11,826	-9,692	-10,968	-26,987	-22,859	-25,426

Next, Hypothesis 7.9 specifies that, in analogy to Hypothesis 7.6, antecedent biotechnology diversity has a positive effect on the rate of biotechnology innovation, as it represents the diversity of biotechnology-specific knowledge. Our estimates do not provide support for this hypothesis. Moreover, the coefficient of bio-antecedent switches sign between models, even though not in a significant way.

According to Hypothesis 7.10alt, parallel to Hypothesis 7.7alt, descendant biotechnology diversity is negatively related to the rate of innovation, again, due to the competitive potential it represents. This hypothesis is fully confirmed by our estimates. Increasing descendant biotechnology diversity with one standard deviation decreases the rate of biotechnology innovation with 9 per cent. As a mirror image this implies that no evidence is found for the legitimation effect predicted by Hypothesis 7.10.

Finally, Hypothesis 7.11 states that, due to the local character of an organization's (technological) search, the biotechnology opportunities encountered by an organization contribute positively to the rate of biotechnology innovation. Again, this hypothesis is fully confirmed by our analysis. Increasing biotechnology opportunities with one standard deviation increases the rate of innovation with 12 per cent.

Regarding our control variables, the number of previous entries has a highly significant positive effect on the rate of biotechnology innovation, implying that favorable entry conditions or serial correlations significantly affect our results. Biotechnology focus does not have a consistent effect on the rate of biotechnology innovation. Both densities (i.e., global and biotechnology) also do not have a consistent effect, but the switch in sign appears to be caused by the difference between our restricted and unrestricted model. Furthermore, the effect of organizational age has a strong positive and significant effect on the rate of innovation in Model 1. The size of the organization, measured by number of employees or assets, also has a positive effect on the rate of biotechnology innovation. In contrast, the amount of revenues seems to have a significant negative effect, while the R&D expenditures have a non-significant positive effect. Finally, with respect to our yearly dummies (not reported here, for the sake of brevity: available upon request), although many years significantly impact the rate of innovation, no clear trend can be identified.

7.6 Discussion and conclusion

In the previous chapter, we have integrated knowledge about the growth and evolution of technology in the theory on the organization-specific technological niche. In doing so, we have considerably extended the theory by adding several theorems. However, even though such a theoretical extension certainly adds to our knowledge, the proof of the pudding is in its eating, or in our case, the empirical validation of hypotheses derived from these theorems. This is, in a nutshell, what this chapter has been about. The pattern of significant findings provides strong support for our extended theory of the organization-specific technological niche. In all, we have found strong support for 6 out of a total of 11 hypotheses (see Table 7.5), which illustrates the importance of a structural perspective towards technological change and organizational innovation.

Clearly, our study is not free of design limitations and, in combination with anomalous findings, provides ground for further research. In the current section, we like to reflect on four of these. First, even though our estimates provide strong evidence for the presence of competitive processes, our estimates do not fully comply with our expectations. More specifically, instead of finding a positive effect that results from the legitimation of the associated design configuration, we find an opposite negative effect for technological crowding. Regarding the effect of non-crowding, our estimates are in line with our expectations. In our view, there are three alternative explanations for our findings, which are: (1) design configurations and associated processes of legitimation and competition are better defined at the component level; (2) biotechnology is in the growth stage of developments, and alternative design configurations exist that aim to overthrow the dominant design configuration; or (3) biotechnology has entered the growth stage of development during our period of observation so that, due to the strong competitive effect, we do not find evidence for legitimation.

Table 7.5 Signs and significance levels of coefficient estimates under alternative specifications

	Models					
Variables	**RE NB R[1]**	**CFE NB R[1]**	**UFE NB R[2]**	**RE NB R[1]**	**CFE NB R[1]**	**UFE NB R[2]**
Crowding†	↓***	↓***	↓***	↓***	↓***	↓***
Non-crowding	↓***	↓***	↓***	↓***	↓***	↓***
Status†	↓	↓***	↓**	↓	↓**	↓**
Quality	↑***	↑***	↑***	↑***	↑***	↑***
Opportunities	↑***	↑***	↑***	↑***	↑***	↑***
Global antecedent diversity	↑***	↑***	↑***	↑***	↑***	↑***
Global focal††	↓	↓**	↓***	↑**	↑	↑***
Global descendant diversity††	↓***	↓	↑***	↓***	↓***	↓**
Bio-antecedent diversity††	↑	↑	↓**	↓	↓***	↓***
Bio-focal diversity	↑***	↑***	↑***	↑***	↑***	↑***
Bio-descendant diversity	↓***	↓***	↓***	↓***	↓***	↓***

Legend: [1]Might suffer from serial correlation; [2] Might suffer from incidental parameters bias; † Not consistent with our hypotheses; †† Coefficient has a switch in sign; * significant at 10%; ** significant at 5%; *** significant at 1%.

Options 2 and 3 both imply that, at this point in time, biotechnology is in the growth stage of technological development. According to our findings in Chapter 4, this is an incorrect assumption. This view is supported by Pisano (2006), who has studied the biotechnology industry in great detail. Moreover, several leading molecular biologists stress the importance of integration through standardization (Botstein, 2004; Endy, 2006; Gray, 2005; Hood, 2004; Sasisekharan, 2005; Sorger, 2004), which signals the lack of a dominant design configuration (cf. Chapter 2). Hence, option 1 is the most likely alternative, which should be given priority in future work. In retrospect, when processes of competition and legitimation are indeed tied to the existence of design configurations at the component level of analysis, it is quite obvious that the same logic does not hold at the system level. After all, while the system is in the seed stage, some of its components can already be in a growth stage of development. Applying our logic at the component level, crowding results in competition and non-crowding in legitimation. However, applying the same logic at the system level, crowding results in legitimation and non-crowding in competition. This gives an obvious contradiction.

Second, contrary to our expectations, we have not found a consistent positive effect for status on the rate of biotechnology innovation. We did, however, find a strong and consistent positive effect for quality. Essentially, the same logic applies here as in our previous discussion about the effect of (non-)crowding. If the assumption is indeed correct that processes of legitimation and competition are tied to design configurations at the component level, then the observation that status can have both a negative and a positive effect is not surprising. As argued, a direct technological tie cannot be uniquely interpreted, which suggests a dual role of technological status. Clearly, the competitive effect is strongest in the growth stage of technological development, when uncertainty is lowest and proximity between the technological developments of two organizations increases competition. In contrast, in the seed stage of technological development, competition occurs between alternative design configurations, which implies that technological proximity does not result in competition, but rather in legitimation of the shared design configuration. Hence, our findings, again, point to the growth stage of technological development, suggesting that we also need to define status at the component level, due to its dual role in technological development. Quite the opposite, technological quality does not have a dual role in technological development, and can be easily aggregated to the system level (as indicated by the strong significant and positive effect).

Third, we have added technological opportunities as a dimension of the technological niche. Obviously, when taking into account different stages of technological development at the component level – as suggested in our discussion of the effects of crowding and status – it is also possible to differentiate between technological opportunities in these different stages of technological development. This connects to the distinction between technological exploration and exploitation in organizational learning (March, 1991). More specifically, in the seed stage of technological development, when developments are geared towards the creation of alternative design configurations, technological opportunities are of a more exploratory nature, and the associated payoffs are more uncertain and distant in time. In contrast, in the growth stage of technological development, progress is more of an exploitative nature, with payoffs that are more certain and proximate in time. The different stages of technological development thus provide rather different sets of technological opportunities. These different sets of opportunities provide yet another dimension to the concept of exploration and exploitation at the organizational level of analysis. Rosenkopf and Nerkar (2001) categorize organizational exploration on the basis of whether its spans organizational and/or technological boundaries. Adding different sets of opportunities to this framework allows for an even more fine-grained analysis of organizational exploration and exploitation.

Fourth, our findings clearly articulate the importance of diversity in technological development from an organizational perspective. Especially antecedent diversity has a strong positive effect on the rate of biotechnology innovation, indicating the important role of prior related knowledge for the organization's absorptive capacity (Cohen & Levinthal, 1990; Van den Bosch et al., 1999; Zahra & George, 2002). This clearly exemplifies the existence of positive spillovers. The fact that biotechnology-specific antecedent diversity (and thus more closely related knowledge) does not have a consistent effect could also be due to the fact that a direct technological tie cannot be uniquely interpreted. Due to its local character, the competitive effect becomes important, clouding the pure effect of knowledge diversity. Regarding global focal diversity, there is a clear distinction between the effects in our restricted versus our unrestricted model. In the restricted model, in accordance with our hypothesis, global focal diversity has a negative effect. However, in the unrestricted model, global focal diversity has a significantly positive effect. This appears to be related to the distinction between the different kinds of organizations included in our restricted and unrestricted models, but further analysis is needed before we can draw strong conclusions. We also found a negative effect of descendant diversity on the rate of biotechnology innovation, with a stronger and more consistent effect at the biotechnology-specific or intra-system level of analysis. This illustrates the localness of competition. However, the fact that global descendant diversity is also significantly negative signifies that competition is not completely localized, and also has a global component. Furthermore, this also implies that our current conceptualization of crowding does not accurately reflect the competitive processes that are taking place within technological landscapes. Moreover, it also points to the importance of taking into account both sides of the lineage of an organization's technology when re-conceptualizing this measure.

Part IV Conclusion

"We're going from looking at the living world as only coming from nature, to a subset of the living world being produced by engineers who design and build hopefully useful living artifacts according to our specifications."

~ *Endy, 2006*

Chapter 8

Conclusion

8.1 Introduction

In this dissertation, we have set out to contribute to the integration of technology within organization science. We have done so by breaking up this objective into manageable task by formulating research questions of which we have tried to answer all but one in the previous chapters. In this chapter, we will pay explicit attention to our final research question, and consider the implications of this dissertation for the study for the co-evolution of technology and organization. We will do so in three steps. First, in Section 8.2, we will explicate the contribution of this dissertation in the context of the wider academic debate in the disciplines of organizational ecology and evolutionary economics. In Section 8.3, we will delineate the limitations that underlie this dissertation and provide avenues for further research. Finally, in Section 8.4, we will reflect in a broader sense on the development in biotechnology.

8.2 Contribution of this dissertation

The main contribution of this dissertation is that, on the basis of ecological insights, we develop a dynamic multi-level model that can be used to empirically study the evolution of an emerging technology. This model is based on the assumption that technology can be effectively studied as a system that is composed of a set of interacting components. Hence, we pay explicit attention to the multi-level and embedded nature of technology. On the basis of these insights, we can actually determine the stage of development of both the system and its components. More specifically, if the focal component interacts in a positive way with the system's other components, the focal component is 'systemic' in the sense that it contributes to the system's (current) stable component configuration. This observation is rather straightforward. After all, if the component is completely independent of the system's configuration, it contributes little to the system's current stable component configuration. Likewise, if the component is negatively related to developments at the system level, it destabilizes the otherwise stable component configuration. Taking this line of reasoning one step further, we hypothesize that when all components contribute positively to the system, a stable component configuration (i.e., a deep structure) can be said to exist at the system level. For example, suppose that we have a technological system that is composed of five technologies (i.e., A to E) over a period of ten years. By examining the interaction between the components and the system (see Table 8.1), it is possible to determine both the stage of development of the individual components and of the system as a whole. That is, components enter the stage of growth when there is a mutualistic relationship between the component and the system as a whole. In turn, the system itself enters a growth stage of development when all components interact positively with the system, hereby forming an integrated whole (period 9 in Table 8.1). Obviously, the requirement that all components need to interact positively to the system is rather restrictive. So, as the name already indicates, a dominant design can be said to exist when the majority of components interact positively to the system (e.g., in period 6 in Table 8.1).[30] Due to the general nature of our model, it is rather easy to include additional levels of analysis (e.g., considering the level of a technological invention, component, system, and landscape in unison), which enables investigating how stable technological design configurations travel upwards in the hierarchy of technology.

Table 8.1 A hypothetical technological system with five component technologies

Technology	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
A				+	+	+	+	+	+	+
B		+	+	+	+	+	+	+	+	+
C							+	+	+	+
D						+	+	+	+	+
E									+	+

The second major contribution of this dissertation stems from the fact that we adopt a two-stage research design. That is to say, by initially abstracting from the organization, we were able to focus all our attention on the evolution of technology. Because technology structures the relationship between organizations, insights derived from this model can subsequently be used to better explain the evolution of organizations. This has already significantly increased our understanding of how processes of legitimation and competition between individual organizations are influenced by technology. On the basis of our model, additional insights in the evolution of technology can be acquired that are relevant to other theory fragments. For example, some of the ideas that come to mind are (1) tying the speed of technological change to the rate of obsolescence in age-dependence theory, (2) tying technological path dependence to structural inertia theory, and (3) using technology to refine density-dependent processes in organizational populations. Our use of formal logic also contributes by connecting to the current formalization wave within organizational ecology, and introducing logical formalization as a tool to integrate different theory fragments.

A third key contribution is that our multi-level model of technology has the potential to close part of chasm in the debate between organizational adaptation (i.e., the dominant perspective in evolutionary economics) and environmental selection (i.e., the

[30] Clearly, here, majority refers to the degree of influence and control of the components, and not just their sheer number.

dominant perspective in organizational ecology). Because the different levels of our model (i.e., invention, component, system, and landscape) can be tied to different levels of organization (i.e., individual organization, population, community, and society), our model can actually be used to tie the different levels of organization to each another (cf. Section 8.4), and hereby connect micro and macro levels of analysis. More specifically, using the different dimensions of the technological niche developed in this dissertation, it is possible to gather data on micro-state adaptations at different levels of analysis of both technology and organization. The data at the different levels of analysis can subsequently be related to one another by using sophisticated multivariate techniques, so connecting the different levels of analysis (e.g., technology-organization, and micro-macro). In time, this obviously leads to a more informed discussion regarding the twin processes of organizational adaptation and environmental selection, which are, after all, just different sides of the same coin. Thus, this study lays some of the foundation for a co-evolutionary framework of technology and organization that is based upon micro-level assumptions and behaviors.

Obviously, this study can only be considered as a first step towards integrating the role of technology within organization science. After all, like any study, this study also suffers from (design) limitations, which provides avenues for further research. This is the topic of our next section.

8.3 Limitations and further research

Even though we have already added value by incorporating technology in one of the domains of organization science (i.e., organizational ecology), because many of our efforts are foundational, more work is still needed to materialize the wealth of added value that still lies hidden. In the current section, our aim is to point to some of this hidden value by delineating the limitations of our study, and by providing directions for future research.

First, even though the model that we have developed is rather simple and general, as of yet, it has little external validity. After all, the fact that we have only considered one technological domain (i.e., biotechnology) significantly hampers the external validity of this study, placing severe limitations on the extent to which we can generalize our findings to other technological domains. Additionally, biotechnology is still emerging, and has not entered the growth stage yet as a deep structure (i.e., a stable design configuration at the system level) is still lacking. This means that there exists a need to further calibrate and refine our model in mature (i.e., non-emerging) technological domains to make sure that we cover the complete emergence process. After all, only mature technologies have a stable design configuration at the system level. Otherwise, we can never be sure that we have observed the full spectrum of the emergence process, implying that vital information might still be missing. Thus, only after this process of further calibration and refinement is completed, this adjusted model can be used to describe and make predictions about the processes that are taking place within emerging technologies. For example, in describing and subsequently predicting how and when stable design configurations emerge at the level of a technological system.

Second, as mentioned previously, we concentrate our attention on emerging technology only, which is merely one side of the story. That is, a complete model of the evolution of technology would obviously also have to include the non-emergence stage(s) of technological development. After all, according to life cycle theory, eventually, technologies mature and decline. Considering the full spectrum of evolution of a technological system implies that we need to take into account the embeddedness of technology more explicitly by considering the configuration of technological systems in the higher level technological landscape. After all, a technological system enters the decline phase as a result of the emergence of an alternative and fitter technological system that effectively competes with the old technological system. So, we need to take into account the interactions between different technological systems more explicitly. When doing so, it is not only important to investigate how the novel technological system competes with the mature system and effectively pushes the mature system into a stage of decline and possibly even complete extinction (i.e., by fully replacing the mature technology and causing it to exit by making it obsolete). Another important question is how the novel technological system arise in the first place (i.e., to study the entry process or founding of novel technological systems). That is, the question how novel technological systems initially emerge deals with another important aspect of the knowledge creation process. In conclusion, a complete analysis would consider how technological systems get born (i.e., by studying the process of entry), grow (i.e., by studying the process of emergence), mature (i.e., by studying the process of diffusion), and die (i.e., by studying the process of exit). Only by considering all these stages in unison can a full view towards the evolution of technology be developed. In doing so, insights and methodologies from organizational ecology would surely be helpful.

When studying the interaction between different technological systems, effective use can be made of social network analysis (Wasserman & Faust, 1994), which provides a methodology and tool set to investigate the interactions between and configurations of actors (whether actors are defined as individuals, organizations, or technological systems). More specifically, through the use of social network analysis, it is possible to identify different "roles" or positions for technological systems in higher-level configurations (Nadel, 1957). For example, through the use of 'blockmodeling' it is possible to partition lower-level elements (i.e., also referred to as actors in social network literature) into discrete sets called positions, and to describe the linkages between these positions using a matrix (Wasserman & Faust, 1994). This methodology is highly similar to Simon's (1962) methodology to decompose complex systems. Using blockmodeling, configuration of higher levels can be build from lower-level elements from the ground up.[31] On the basis of these configurations, it is possible to define several characteristics. For example, it is possible to classify the configuration to so-called ideal types that display theoretically important structural properties (Wasserman & Faust, 1994). Because it lies beyond the objective of this chapter to dig deep into these ideal types, we refer to the social network literature instead.

To give a simple example, it is possible to distinguish between the core and peripheral structure of a technological landscape. This would enable an analysis of strategic and non-strategic technologies, as strategic technologies are believed to have strong linkages (i.e., interactions) with alternative technologies and will, therefore, eventually, take on a core or central position in the technological landscape. Clearly, this is just one simple example of how network analysis can be used as a tool to examine the evolution of technology. A more sophisticated decomposition of the technological landscape could enable delineating stable configurations or constellations of technological systems (e.g., technological paradigms), where multiple roles (i.e., different technological types) could be identified that fulfill different functions (e.g., integration, coordination, communicate, facilitate, support, and so on and so forth). Most likely, these different types will display different kinds of evolutionary processes such as, for example, the speed with which they grow and evolve. Even though it is argued extensively that different types of technologies exist (e.g., many scholars argues that emerging strategic technologies fuel economic growth and development), empirical studies that distinguish between different types of technology are extremely rare. By considering the embedded nature of technology, it is possible to identify the different types. This is important because, if we want to truly understand the evolution of any level (e.g., system), we also have to consider the higher (e.g., landscape) level in which the system is embedded, besides the lower (e.g., component) levels which it comprises (Baum, 1999). After all, because all evolution is really co-evolution (Kauffman, 1993), we have to take into account the adjacent levels to investigate how these levels co-evolve. This effectively leads to a hierarchically nested model in which adjacent levels co-evolve (Baum & Singh, 1994a).

In such a hierarchically nested model of technology, the major levels of analysis that can be defined are: (1) technological landscape – a configuration of a set of technological systems; (2) technological system – a configuration of a set of technological

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[31] In the current study, we have used the classification system of the USPTO to define the components of our technological system (i.e., biotechnology). A valid question is whether this classification is the optimal representation of any technological domain. Future research could determine the appropriateness of this representation by building an alternative classification on the basis of what is called blockmodeling. It is then possible to determine whether this alternative classification is a better representation of reality through a comparative study along the lines of our study in Chapter 4.

components; (3) technological component – a configuration of a set of technological inventions; and (4) technological invention – a configuration or a set of antecedent inventions and ideas. This nested hierarchy of technology is represented in Figure 8.1.

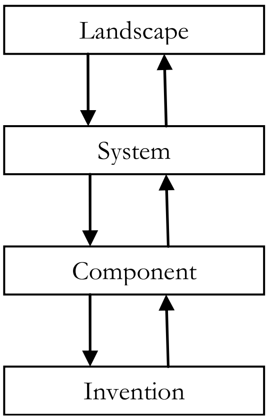

Figure 8.1 Hierarchical model of technology

In view of this hierarchical model, and keeping in mind that each level of aggregation (i.e., all levels except invention) can effectively be defined as a configuration of lower level elements, some research questions that come to mind are: How does stability (i.e., stable design configurations) travel upwards (i.e., upward causation)? Related to this question is also how stability at higher levels gets 'overthrown' by changes at lower levels. And also, what are the different 'roles' or functions that lower levels (e.g., systems) can take on in higher levels (e.g., landscapes)? To go in the other direction, we can also ask how higher levels guide the evolution of lower levels (i.e., downward causation)? Or, when considering both directions in unison, how do the different stages of evolution (i.e., convergence and divergence or seed and growth) interact at different levels of analysis (i.e., co-evolution or simultaneous upward and downward causation)? Regarding this latter research question, if the observation is indeed correct that stability travels upwards and that stable configurations at a higher level can only be composed of stable lower-level elements, this implies that convergence at higher levels is only possible if there exists convergence at the lower levels that make up the higher level. In the context of biotechnology this would imply that biotechnology can enter a stage of convergence only when its component technologies are also in a stage of convergence. Investigating these issues should be high on the agenda of future research, as this has the potential to provide valuable insights into the evolution of technology.

Third, in this dissertation, by considering both technology and organization, we generate important insights that already provide directions for highly specific and incremental extensions in future research (e.g., see Chapters 3 to 7). However, due to our two stage-research design, we consider technology and organization separately. When studying technology and organization simultaneously, additional value can be created.

For example, by distinguishing between the different stages of development for technology and considering the organization's strategy towards this technology, we can construct the following matrix in Figure 8.2 (this is a copy of Figure 4.3).

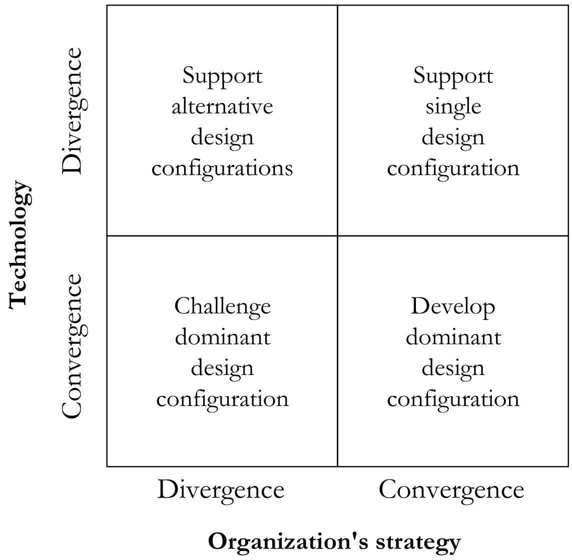

Figure 8.2 The organization's strategy and stages of technological development

According to this matrix, there are essentially four basic strategies for the organization, which are: (1) support alternative design configurations, (2) create dominant design configurations, (3) challenge dominant design configuration, and (4) develop dominant design configuration. Clearly, this matrix cannot only be used to classify any individual organization at a single point in time, but can also be used to describe (a population of) organizations over time. By being able to classify technology into different stages of development, some of the research questions that can be further investigated are: Which strategies fit which organizations? When is the appropriate time to switch strategies for individual and groups of organizations? What causes the transition between the different stages of technological evolution? And, when is the dominant configuration overthrown?

Notwithstanding the added value of either considering multiple levels of technology (see Figure 8.1) or considering technology and organization in unison, a true co-evolutionary model of technology and organization would need to consider both issues simultaneously. To do so, it is possible to tie the different levels of technology to different levels of organization. After all, technology and organization co-evolve at different of analysis. This logic is displayed in Figure 8.3.

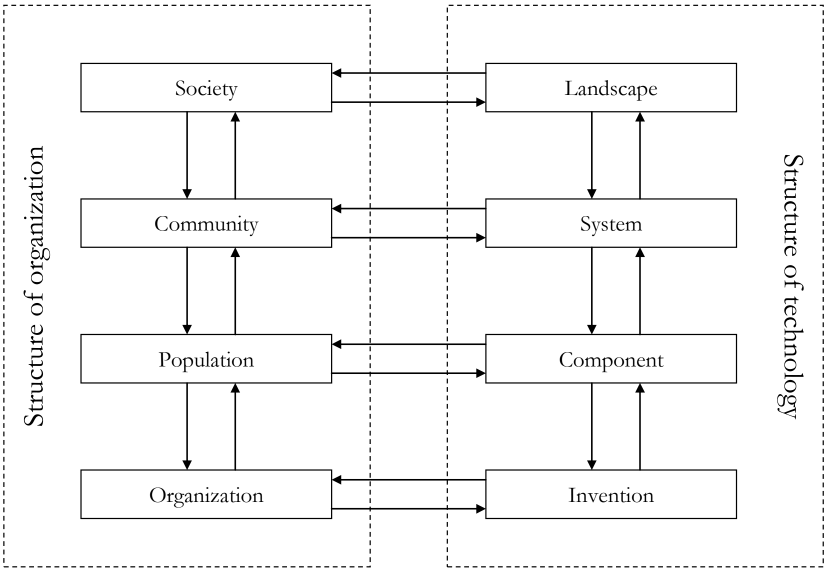

Figure 8.3 A hierarchical co-evolutionary model of technology and organization

Within this framework, each level is a configuration of lower-level elements. So, a society can be considered as a configuration (i.e., an ordered set) of organizational communities, while a community is a configuration of organizational populations, and a population is a configuration of individual organizations. Finally, from a purely technological perspective, an individual organization can be defined as a configuration of a set of technological inventions. As mentioned, stable technological configurations play an important role in the evolution of both technology and organization at multiple levels of analysis. Initially, organizations (at multiple levels of analysis) create a stable technological configuration, which enables cumulative progress through specialization (i.e., defining elements by creating boundaries between them) and integration (i.e., creating interfaces between isolated segments). However, this very same process that facilitates cumulative changes, also creates inertia (Baum & Singh, 1994a). Hence, the stable technological configuration starts directing organizational and technological evolution through a self-reinforcing and path-dependent process. So, we can define stable technological configuration at each level of analysis, as visualized in Figure 8.4.

Regarding the different levels of analysis, at the organizational level, a set of technological inventions is created by an organization to generate revenues in the marketplace. Over time, the organization becomes dependent on the subset of inventions that generate the bulk of its revenues, to which we can refer as the organization's technological core. At the population level, organizations collectively contribute to the development of a technological component (i.e., configuration of a set of related technological inventions). At a certain point in time, the organizations collectively agree upon the performance characteristics of this component that determines the configuration of this component, also known as a dominant design (Abbernathy & Utterback, 1978), hereby effectively locking-in the stable component configuration that subsequently guides evolution. At the community level of analysis, stakeholders in the technology jointly contribute to the development of technological systems (i.e., configuration of a set of technological components). According to Tushman and Romanelli (1985), after substantial experimentation, a stable design configuration emerges as a synthesis of a large number of proven concepts. This stable configuration connects to the notion of a technological paradigm (i.e., configuration of a set of technological systems), characterized by stable and predictable patterns of growth and development. Even though we acknowledge that this definition is different from Dosi's (1982) notion of a technological paradigm, the concept of a paradigm is naturally tied to the notion of a community (Kuhn, 1996). Finally, at the level of a society, within a technological landscape, developments can be characterized by a direction as well (e.g., the miniaturization and digitalization of technology), implying the existence of meta-paradigms (Nightingale, 2008). However, we prefer the notion of a technological regime (Nelson & Winter, 1982) (i.e., a configuration of a set of paradigms), as this term naturally connects with the direction of general developments in a society.

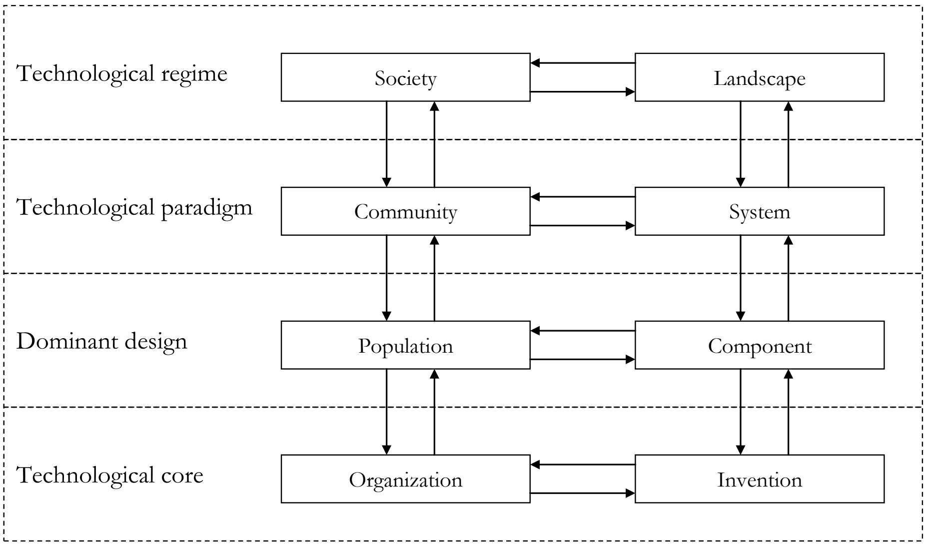

Figure 8.4 Stable technological configurations at multiple levels of our hierarchical co-evolutionary model

Studying the co-evolution of technology and organization on the basis of these stable configurations definitely provides important insights, as "[I]t is the information about stable configurations […] that guides the process of evolution" (Simon, 1962: 473). To illustrate, these stable configurations at individual horizontal levels of analysis already directs our attention to numerous associated research questions. For example, on the one hand, this framework suggests to study how the technological environment influences the rate at which new organizations and new organizational forms are created, the rates at which existing organizations and organizational forms die out, and the rate at which organizations change forms (Baum & Singh, 1994a). On the other hand, this framework also points to the study of how the organizational environment influences the rate at which new technological components and systems are created, the rate at which existing technological components and systems die out, and the rate at which technologies change. While treatment of either the technological or the organizational environment as exogenous to the other is a useful starting point, a true co-evolutionary approach abstains from the traditional focus on independent and dependent variables in favor of viewing each variable as influencing the other (Baum & Singh, 1994a). Hence, developing a theory of the co-evolution of technology and organization requires examining the causes of stability and change in both organizational and technological entities at different levels of analysis simultaneously, and investigating the forces that isolate different entities from each other (Baum & Singh, 1994a). Obviously, listing all possible research questions by applying such a co-evolutionary perspective is undoable. So, instead, we list some of the generic characteristics that can be defined at each level within each hierarchy (i.e., excluding individual inventions).

By defining each levels as a configuration of lower-level elements, we can use the framework of Henderson and Clark (1990) to identify different types of changes (see Table 8.2). After delineating the different types of changes at different levels of analysis, it is possible to relate these changes at different level to one another to analyse processes of upward and downward causation. For example, how lower level incremental changes result in radical changes at higher levels due to the fact that evolution is faster at lower levels of analysis (Baum, 1999) or, alternatively, how stability (i.e., incremental changes) travels upwards. Obviously, such analyses would also require looking at the structural characteristics that facilitate or constrain these changes.

Table 8.2 Systemic changes (adapted from Henderson & Clark, 1990)

		Core positions	
		Reinforced	**Overturned**
Linkages	**Unchanged**	Incremental change	Modular change
	Changed	Architectural change	Radical change

Some general characteristics that can be considered in such an investigation are: (1) crowding or niche overlap (i.e., the overlap between elements or configurations), (2) the position of a lower level element in higher level configurations (e.g., status, prestige, core/non-core, and centrality), (3) density (or the number of positions in a configuration), (4) stage of development (i.e., divergence and convergence, and (5) diversity (i.e., the extent to which the configuration is diverse; this can be determined from multiple perspectives). In addition, when applying a dynamic perspective (i.e., by considering configurations over time), additional properties can be defined: (1) stability or rates of change, which is the extent to which the configuration and the elements therein change, as reflected in the entry and exit of positions and elements occupying positions, and their relative positions to one another (e.g., status, centrality, hierarchy, and dominance); (2) performance, which is the positional change of an element within the higher level configuration (e.g., from core to non-core); and (3) stage transitions, which is the extent to which levels transition from convergence into a divergence stage and vice versa (this naturally connects to the different kinds of changes identified in Table 8.6).

Clearly, next to these generic characteristics that can be defined at multiple levels of analysis, we can also define numerous specific characteristics that apply only to single or some levels, for example, at the level of individual inventions, it is possible to determine the success of an invention. For example, by determining the relative number of citations that the invention receives over a certain period (Fleming, 2001). At the level of an individual component or organization, it is possible to transform this variable into the number of blockbusters that enter the component or the organization. Another example of a specific characteristic is the nature of an organization's technological search behavior for example, by distinguishing between exploration and exploitation.

On the basis of both the general and specific characteristics, intricate theories can be developed regarding the co-evolution of technology and organization. Additionally, over time, on the basis of general characteristics, universal theories might even be developed that apply universally to other co-evolutionary hierarchical systems as well, such as, for example, in studying the co-evolution between (1) political and organizational systems, (2) social and technological systems, (3) biological and technological systems, or (4) scientific and technological systems. After all, complexity often takes the form of hierarchy, and hierarchical systems have common properties independent of specific content, which implies that it might not be complete vain to search for common properties among diverse kinds of systems (Simon, 1962).

8.4 Broader reflections on the evolution of biotechnology

In a broad sense, biotechnology refers to all technology of the living world, implying that it has already been around for quite some time. Human kind started to use biological process over 6000 years ago for the making of bear, bread, and wine. Patent data also demonstrate the old age of biotechnology, as the first biotechnology patent at the USPTO dates back to the beginning of the 19th century (i.e., 1836). This was actually one of the first patents ever granted (i.e., patent number 245), and is entitled "improvement in managing saccharine, vinous, and acetous fermentation". Obviously, because the biotechnological underpinnings of this patent (i.e., the precise workings of the molecular processes) were not yet known, this patent was first classified in another class. However, because this patent effectively uses biological processes for fermentation purposes, this patent was later reclassified by the USPTO as a biotechnology patent (i.e., into class 435, to be precise). After all, awareness about biotechnology only really started roughly a century ago, when the word biotechnology was first used in print in 1919 by the

Hungarian agricultural engineer Karl Ereky, who defined biotechnology as "any product produced from raw materials with the aid of living organisms" (Meyer, 2003). Commercial interest really started after the creation of the first biotechnology organization (i.e., Genentech), which was founded over three decades ago in 1976. Since then, we have witnessed a surge in new entrants, with currently over 1,450 active companies in the USA alone (BIO, 2008).

However, despite this long history, biotechnology has not yet delivered on its promise (Pisano, 2006). Academics, industry, and government have widely accepted and promoted the biotechnology revolution, which has generated strong expectations about major breakthroughs in healthcare and medicine (Nightingale & Martin, 2004). Some even posit biotechnology as the solution to increasing healthcare costs and the ageing of our society (Termeer, 2002). Biotechnology was (and still is, for that matter) expected to radically alter the drug discovery process – initially through technologies such as recombinant DNA and monoclonal antibodies, and later through the technologies of gene therapy and stem cells – by providing a set of first principles that enables a more rational (less random) drug discovery process (Pisano, 2006). However, certain set-backs and obstacles have proven to be rather difficult to overcome in a timely fashion as to meet expectations (Jones, 2005). To illustrate, comparing pharmaceutical productivity with biotechnology productivity reveals no striking dissimilarities (Pisano, 2006). According to Nightingale and Martin (2004) it becomes clear from a variety of indicators that output has failed to keep pace with the increase in R&D spending, and biotechnology displays the well-established pattern of slow and incremental technology diffusion, instead of the expected revolutionary changes. However, the overly optimistic expectations already had a considerably influence on policy-making. Therefore, many assumptions that underlie much contemporary policymaking at the OECD, in the USA, the UE, and developing countries seriously need to be rethought (Nightingale & Martin, 2004), as biotechnology currently does not display the cumulative growth that was expected.

But why has biotechnology not been able to deliver on (so many of) its promises? As mentioned, a paradigm is missing at the system level. That is, components are still being added and developed, and alternative design configurations compete for dominance, at the expense of truly cumulative developments. Due to the lack of a paradigm, a common vocabulary is missing that prevents people from different disciplines to effectively communicate with each other, which severely hinders the sharing of knowledge and information. Consider, for example, a recent survey on biotechnology regulations by the OECD (Beuzekom & Arundel, 2006) – which boasts that it 'plays a prominent role in fostering good governance' and 'helps governments to ensure the responsiveness of key economic areas with sectoral monitoring', where all efforts were effectively thwarted by inconsistent definitions of biotechnology (Miller, 2007: 58).

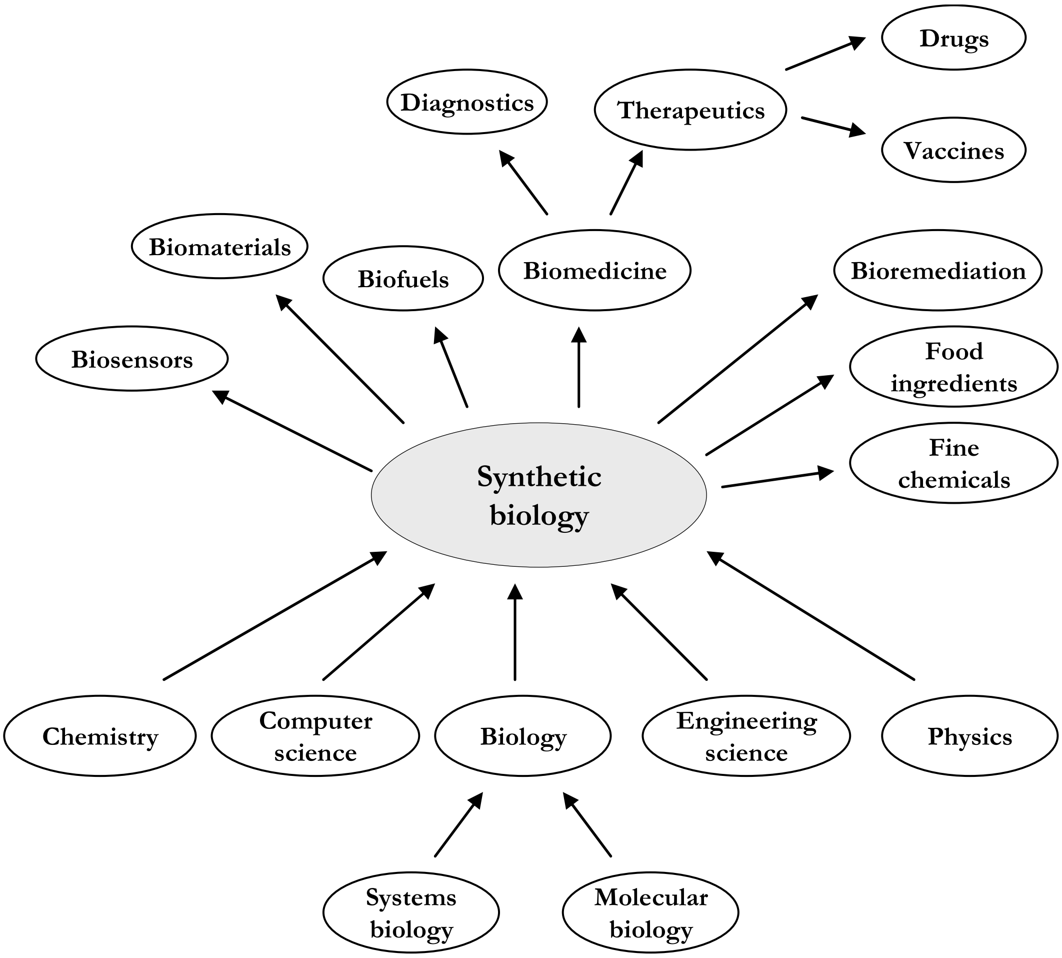

Figure 8.5 Synthetic biology (source: http://www.synthetic-biology.info)

The reason why a paradigm is still missing is that each new major technological wave impacts the existing technological structure (or landscape) at increasingly deeper levels. Biotechnology is a strategic technology (Bauer, 2005; Gaskell, 2000) that is at the forefront of a new major technological wave that impacts many technological systems, and even has the potential to change the basic configuration of the technological landscape. To illustrate the connectedness of biotechnology, consider the relatedness of synthetic biology in Figure 8.5. It becomes clear from this figure that biotechnology is tied to many different kinds of technologies such as, for example, energy, food, drugs, electronics, and chemicals. Because biotechnology is related to a diverse set of technologies, it takes a long time to develop all the interfaces needed to interact with these different technologies (i.e., to integrate biotechnology in the technological landscape). So, biotechnology's complexity not only stems from the fact that it is composed of a set of highly complex and heterogeneous set of interacting components (Pisano, 2006), but also because biotechnology's components are interacting with components in many other technological systems. As a result, biotechnology encompasses a broad constellation of technologies, methodologies, and disciplines (Pisano, 2006).

Moreover, each new technological wave not only impacts technology at increasingly deeper levels, but also society as a whole. If we defining society as a nested hierarchy of interconnected ideas (Nightingale, 2008), then biotechnology can be argued to challenge this hierarchy at its most basic level (i.e., at the level of basic assumptions and belief systems). As a result, it challenges many existing ideologies and dogmas that are built around these basic assumptions and belief systems. This obviously results in fierce opposition from many layers of society that effectively try to resist many changes that biotechnology enables. Because societies (or any system, for that matter) do not change overnight (Popper, 1963), only when pressure is build up to unacceptable levels is change forced through (Kuhn, 1996; Nightingale, 2008). This implies that many developments within biotechnology need to struggle for legitimation, conquering numerous obstacles along the way. To illustrate, stem cell research has created a political firestorm in the USA (Jones, 2005), and has climaxed in a ban of federal funding of stem cell research by former President Bush in 2001 (Stolberg, 2007). Fortunately, this has just recently been undone by President Obama (Lite, 2009). In addition, biotechnology fuels the discussion regarding the gap between have's and have not's in the context of human improvement through biomedical technologies (Kass, 2003), while genetically engineered food faces strong opposition from social movements – e.g., Greenpeace, the Foundation on Economic Trends, and the Union of Concerned Scientists continue to militate against the most benign and beneficial uses of genetically engineered food, such as "golden rice" (Miller, 2007).[32]

Another hurdle concerns the debate about the possibility of patenting genes and proteins. This is related to what is known as the "anti-commons" phenomenon (Barfield & Calfee, 2007), and circles around whether private ownership of scientific discovery hampers future developments – i.e., whether the privatization of scientific information is too far upstream in the development pathway, and distant from practical products (Korn & Heinig, 2002), so that it hampers future developments. Even though research concludes that the "anti-commons" problem is not really an issue, it has already driven much policy recommendations and generated a lot of uncertainty that hampers developments (Barfield & Calfee, 2007).

Another obstacle lies within the domain of safety. According to Endy, Thomas, and Brand (2008), current security levels severely restrict the sharing of genetic information and material. This is related to terrorist threats. Consider, for example, the threat involved when a hemorrhagic fever like Ebola can be downloaded freely from the

[32] Golden rice is a genetically engineered rice with increases nutritional value to alleviate some of the life-threatening micronutrient deficiencies in developing countries (see http://www.goldenrice.com).

internet and the DNA encoding (i.e., DNA synthesis) could be purchased for $20,000 (Endy et al., 2008). Recently, the Spanish flu, a virus that killed over 50 million people in the last century, was synthesized using synthetic biology after the issue was extensively scrutinized by the US National Science Advisory Board for Biosecurity. The reason to do so was that, despite the obvious threat that this might pose, no disease has ever been cured in secret. However, in an editorial in the New York Times, Bill Joy and Ray Kurzweil argued that this was an extremely foolish act because the release of this virus could be much worse than an atomic bomb (Kurzweil & Joy, 2005), which exemplifies the existence of serious concerns among the general public.

Next, we will provide several suggestions that could contribute to developments within biotechnology. First, as mentioned in Chapter 2, biotechnology can be simplified by breaking it apart and creating simple interfaces between the individual pieces (Baldwin & Clark, 2000; Endy, 2005). That is, complex problems (or systems, for that matter) can be managed by dividing them up into smaller pieces and looking at each piece separately. Once a problem is broken up, the complexity can be hidden behind an abstraction and an interface. Obviously, one needs to break apart the system at natural points (i.e., at the joints), so that the parts are relatively independent from one another, and can be studied rather independently. This also connects to the engineering principles of abstraction, decoupling, and standardization (cf. Chapter 2). Then, when the complexity has been hidden in the (black boxes of the) components, it will be possible to bring biotechnology to the masses, which is required to unleash the full potential of biotechnology. This connects to the open-innovation paradigm of crowd-sourcing, which implies that developments within biotechnology are supported by the potential creativity that resides in the "crowd". This is similar to the developments within the ICT industry and the internet revolution. Here, cumulative development only became fully possible when every household had a computer (i.e., the technology was effectively hidden in a black-box and a simple user interface was created to allow use the technology), and anybody could effectively start his or her own computer or internet company from his or her own garage. In a similar vein, garage biotechnology will lead to a true biotechnology revolution (Kuldell & Shetty, 2009). The current trend towards an open government in the USA connects rather nicely to this point. For example, the USPTO recently concluded a pilot project called peertopatent.org, where they effectively used a community of experts to assist in the patent review process to increase transparency, reduce cost, and increase patent strength for litigation purposes.

Clearly, another important point is the close monitoring of biotechnology developments (e.g., output indicators) to make sure that policies are aligned with actual developments, instead of relying on naïve and optimistic promises (Nightingale & Martin, 2004) from the past or high-profile horror or success stories (Miller, 2007).

Some final thoughts

During the last twenty years, scientists have been working on the digitalization of biology – i.e., the reading of DNA (Venter, 2008). Recently, DNA synthesis foundries manufactured (or write) synthetic DNA (sDNA) for genetic engineers and synthetic biologists. DNA sequences that are increasing in length can be ordered over the internet and delivered within two weeks (ETC, 2007). This effectively allows scientists and practitioners to recombine genetic material and build sDNA into novel combinations with endless possibilities (we have already discussed some of these possibilities in Chapter 2). These developments bring us closer and closer to redesigning life as we know it, and the ability to create and redesign entire species. Obviously, this will continue to raise a plethora of ethical issues that need to be resolved before progress can be made. Personally, I do not see why we should not continue in this direction. After all, this will bring us closer to a true understanding of life on earth and the uniqueness of our beings. Moreover, eventually, true scientific insight in the nature of life as we know it (i.e., the technology of the external living world) will enable a leap forward in human consciousness (i.e., the technology of the internal living world).

Appendices

Appendix A

Technological categories and domains

Table A.1 Technological categories and domains (source: Source: Hall, Jaffe, & Trajtenberg, 2001b)

1	**Chemicals**	
	11	Agriculture, Food, Textiles
	12	Coating
	13	Gas
	14	Organic Compounds
	19	Miscellaneous - Chemical
2	**Computers & Communications**	
	21	Communications
	22	Computer Hardware & Software
	23	Computer Peripherals
	24	Information Storage
3	**Drugs & Medical**	
	31	Drugs
	32	Surgery & Medical Instruments
	33	Biotechnology
	39	Miscellaneous - Drugs & Medical
4	**Electrical & Electronic**	
	41	Electrical Devices
	42	Electrical Lighting
	43	Measuring & Testing
	44	Nuclear & X-rays
	45	Power Systems
	46	Semiconductor Devices
	49	Miscellaneous – Electrical & Electronic
5	**Mechanical**	
	51	Materials Processing. & Handling
	52	Metal Working
	53	Motors, Engines & Parts
	54	Optics
	55	Transportation
	59	Miscellaneous - Mechanical
6	**Others**	
	61	Agriculture, Husbandry, Food
	62	Amusement Devices
	63	Apparel & Textile
	64	Earth Working & Well
	65	Furniture, House Fixtures
	66	Heating
	67	Pipes & Joints
	68	Receptacles
	69	Miscellaneous - Others

Appendix B

Descriptive statistics technological domains

Tables

B.1 Status rank of technological domains
B.2 Status of technological domains
B.3 Growth rate of patents in percentages of previous period
B.4 Number of patents in technological subcategories in different periods
B.5 Percentage of patents in technological subcategories in different periods
B.6 Ranking on the basis of share of total patents per period

Legend

P0: period prior to 1976
P1: period from 1976 – 1980
P2: period from 1981 – 1985
P3: period from 1986 – 1990
P4: period from 1991 – 1995
P5: period from 1996 – 2000
P6: period from 2001 – 2005

Table B.1 Status rank of technological domains

Technological domain	P0	P1	P2	P3	P4	P5	P6	Total
11 Agriculture, Food, Textiles	3	6	4	6	3	5	6	5
12 Coating	9	10	13	14	13	14	15	14
13 Gas	31	29	30	32	33	34	34	34
14 Organic Compounds	2	1	2	2	2	2	4	2
19 Miscellaneous-chemical	1	2	1	1	1	1	1	1
21 Communications	10	9	9	7	5	3	3	3
22 Computer Hardware & Software	15	14	14	11	6	4	2	4
23 Computer Peripherals	30	31	29	26	24	21	21	22
24 Information Storage	19	17	20	20	20	12	14	16
31 Drugs	24	23	16	18	15	15	18	18
32 Surgery & Medical Instruments	29	28	25	21	17	11	9	12
33 Biotechnology	33	33	33	31	26	23	23	25
39 Miscellaneous-Drug&Med	34	34	34	34	34	28	27	29
41 Electrical Devices	4	4	6	5	8	9	7	8
42 Electrical Lighting	20	20	26	25	25	26	24	26
43 Measuring & Testing	12	12	10	10	11	13	12	11
44 Nuclear & X-rays	18	16	17	17	21	22	22	21
45 Power Systems	7	7	7	9	10	8	5	7
46 Semiconductor Devices	22	21	23	22	19	18	8	13
49 Miscellaneous-Elec.	14	15	15	15	16	17	19	17
51 Materials Processing. & Handling	5	3	3	3	4	6	10	6
52 Metal Working	11	11	12	13	12	16	17	15
53 Motors, Engines & Parts	13	13	11	12	14	20	20	19
54 Optics	17	19	19	16	18	19	16	20
55 Transportation	16	18	18	19	22	25	26	23
59 Miscellaneous-Mechanical	8	8	8	8	9	10	13	10
61 Agriculture, Husbandry, Food	28	27	28	28	28	27	28	27
62 Amusement Devices	35	35	35	35	35	35	35	35
63 Apparel & Textile	32	30	32	33	31	32	32	32
64 Earth Working & Well	26	26	27	30	32	33	33	33
65 Furniture, House Fixtures	27	32	31	29	30	30	29	31
66 Heating	23	24	24	27	27	29	30	28
67 Pipes & Joints	25	25	22	24	29	31	31	30
68 Receptacles	21	22	21	23	23	24	25	24
69 Miscellaneous-Others	6	5	5	4	7	7	11	9

Table B.2 Status of technological domain (%)

Technological domain	P0	P1	P2	P3	P4	P5	P6	Total
11 Agriculture, Food, Textiles	6.16	5.32	5.28	4.95	5.50	4.95	4.48	4.87
12 Coating	3.66	3.37	3.12	2.81	2.94	2.89	2.81	2.89
13 Gas	0.90	0.95	0.91	0.79	0.73	0.53	0.46	0.59
14 Organic Compounds	9.86	13.13	11.60	8.89	8.34	7.52	5.97	7.52
19 Miscellaneous-chemical	12.1	12.52	12.29	11.64	11.65	10.78	10.31	10.92
21 Communications	3.56	3.62	3.81	4.52	4.95	6.84	7.38	6.31
22 Computer Hardware & Software	2.07	2.35	2.98	3.97	4.77	5.71	7.41	5.86
23 Computer Peripherals	0.90	0.85	0.95	1.20	1.44	1.97	2.03	1.76
24 Information Storage	1.77	1.79	1.70	1.88	2.18	3.10	3.02	2.71
31 Drugs	1.21	1.44	2.00	2.10	2.59	2.84	2.50	2.49
32 Surgery & Medical Instruments	0.93	1.01	1.30	1.82	2.41	3.42	3.86	3.12
33 Biotechnology	0.56	0.61	0.73	0.79	1.15	1.71	1.85	1.52
39 Miscellaneous-Drug&Med	0.19	0.22	0.34	0.41	0.64	1.02	1.08	0.87
41 Electrical Devices	6.11	5.49	5.02	4.98	4.27	3.84	3.97	4.19
42 Electrical Lighting	1.74	1.54	1.21	1.28	1.29	1.29	1.50	1.39
43 Measuring & Testing	3.02	3.08	3.38	4.01	3.65	3.09	3.54	3.45
44 Nuclear & X-rays	1.90	1.89	1.87	2.11	2.10	1.90	1.91	1.95
45 Power Systems	4.80	4.35	4.43	4.25	3.94	4.02	4.67	4.34
46 Semiconductor Devices	1.35	1.50	1.44	1.79	2.19	2.66	3.86	2.92
49 Miscellaneous-Elec.	2.35	2.21	2.16	2.47	2.44	2.75	2.42	2.49
51 Materials Processing. & Handling	6.04	5.67	5.46	5.32	5.03	4.32	3.71	4.36
52 Metal Working	3.19	3.08	3.18	3.16	2.99	2.75	2.56	2.78
53 Motors, Engines & Parts	2.92	3.01	3.30	3.20	2.65	2.10	2.05	2.35
54 Optics	2.01	1.66	1.83	2.11	2.36	2.22	2.57	2.33
55 Transportation	2.01	1.77	1.86	2.09	1.84	1.52	1.40	1.59
59 Miscellaneous-Mechanical	4.63	4.08	4.21	4.31	3.97	3.69	3.22	3.63
61 Agriculture, Husbandry, Food	1.02	1.04	1.09	1.08	1.04	1.03	0.78	0.93
62 Amusement Devices	0.11	0.19	0.18	0.20	0.21	0.31	0.41	0.32
63 Apparel & Textile	0.89	0.91	0.80	0.78	0.77	0.70	0.59	0.69
64 Earth Working & Well	1.08	1.04	1.19	0.88	0.75	0.54	0.53	0.65
65 Furniture, House Fixtures	1.05	0.81	0.81	0.99	0.87	0.80	0.74	0.80
66 Heating	1.29	1.32	1.41	1.09	1.06	0.80	0.70	0.87
67 Pipes & Joints	1.14	1.26	1.44	1.39	1.04	0.70	0.65	0.84
68 Receptacles	1.70	1.47	1.48	1.68	1.73	1.58	1.40	1.53
69 Miscellaneous-Others	5.72	5.45	5.22	5.06	4.51	4.08	3.66	4.17

Table B.03 Growth rate of patents in percentages of previous period

Technological domain		P1	P2	P3	P4	P5	P6	Average
11	Agriculture, Food, Textiles	44	120	130	108	131	104	106
12	Coating	38	108	114	132	127	101	103
13	Gas	39	111	101	90	129	119	98
14	Organic Compounds	38	83	101	127	102	95	91
19	Miscellaneous-chemical	40	103	111	121	113	102	98
21	Communications	39	101	172	132	180	147	128
22	Computer Hardware & Software	48	144	204	160	247	147	158
23	Computer Peripherals	75	155	185	137	231	157	157
24	Information Storage	39	125	169	151	179	133	133
31	Drugs	103	107	145	130	171	100	126
32	Surgery & Medical Instruments	51	129	183	154	147	106	128
33	Biotechnology	56	139	170	179	270	99	152
39	Miscellaneous-Drug&Med	55	130	157	122	150	121	122
41	Electrical Devices	27	112	123	108	140	138	108
42	Electrical Lighting	31	106	156	114	129	150	114
43	Measuring & Testing	37	108	137	109	125	131	108
44	Nuclear & X-rays	40	95	182	110	86	147	110
45	Power Systems	35	107	119	111	150	137	110
46	Semiconductor Devices	48	116	204	202	186	183	157
49	Miscellaneous-Elec.	40	118	142	110	136	103	108
51	Materials Processing. & Handling	31	92	118	108	109	102	93
52	Metal Working	34	92	132	103	102	110	95
53	Motors, Engines & Parts	37	115	120	100	115	123	102
54	Optics	45	102	137	129	153	115	113
55	Transportation	33	95	137	109	120	129	104
59	Miscellaneous-Mechanical	29	100	138	105	115	106	99
61	Agriculture, Husbandry, Food	36	96	128	109	112	92	96
62	Amusement Devices	42	88	130	143	126	114	107
63	Apparel & Textile	29	99	117	96	130	83	92
64	Earth Working & Well	36	104	109	98	101	119	94
65	Furniture, House Fixtures	35	90	151	110	131	99	103
66	Heating	42	119	88	81	110	97	90
67	Pipes & Joints	33	107	111	98	122	106	96
68	Receptacles	31	95	149	107	118	79	96
69	Miscellaneous-Others	32	99	127	109	120	102	98

Table B.4 Number of patents in technological domains in different periods (in thousands)

Technological domain		P0	P1	P2	P3	P4	P5	P6	Total
11	Agriculture, Food, Textiles	17.4	7.6	9.2	12.0	13.0	17.0	17.7	93.8
12	Coating	12.7	4.8	5.2	5.9	7.8	9.9	10.0	56.4
13	Gas	4.7	1.8	2.0	2.0	1.8	2.4	2.8	17.7
14	Organic Compounds	85.2	32.7	27.3	27.6	35.0	35.6	33.9	277.3
19	Miscellaneous-chemical	88.3	35.7	36.9	40.9	49.5	55.8	56.8	363.9
21	Communications	27.4	10.7	10.8	18.5	24.4	44.0	64.9	200.7
22	Computer Hardware & Software	9.4	4.5	6.5	13.2	21.1	52.2	76.9	183.8
23	Computer Peripherals	1.7	1.3	2.0	3.6	5.0	11.5	18.0	43.0
24	Information Storage	9.0	3.5	4.4	7.3	11.1	19.9	26.4	81.5
31	Drugs	8.8	9.1	9.8	14.2	18.4	31.3	31.4	123.1
32	Surgery & Medical Instruments	9.7	4.9	6.4	11.6	17.9	26.4	27.9	104.7
33	Biotechnology	2.9	1.6	2.3	3.9	6.9	18.6	18.4	54.6
39	Miscellaneous-Drug&Med	2.6	1.4	1.8	2.9	3.5	5.3	6.4	23.9
41	Electrical Devices	45.0	12.3	13.7	16.9	18.2	25.5	35.1	166.7
42	Electrical Lighting	14.3	4.4	4.7	7.3	8.2	10.6	15.9	65.5
43	Measuring & Testing	24.1	8.9	9.6	13.2	14.4	17.9	23.5	111.4
44	Nuclear & X-rays	11.4	4.6	4.4	7.9	8.7	7.5	11.0	55.4
45	Power Systems	32.0	11.2	12.0	14.3	15.9	23.8	32.6	141.9
46	Semiconductor Devices	6.2	3.0	3.5	7.1	14.3	26.6	48.6	109.1
49	Miscellaneous-Elec.	10.5	4.2	4.9	7.0	7.7	10.4	10.7	55.3
51	Materials Processing. & Handling	63.9	20.1	18.4	21.8	23.5	25.5	25.9	199.3
52	Metal Working	33.8	11.4	10.4	13.7	14.1	14.4	15.8	113.6
53	Motors, Engines & Parts	33.7	12.5	14.3	17.2	17.1	19.7	24.2	138.7
54	Optics	15.1	6.7	6.9	9.4	12.1	18.5	21.2	89.9
55	Transportation	30.2	9.9	9.4	12.8	14.0	16.8	21.6	114.7
59	Miscellaneous-Mechanical	53.7	15.7	15.7	21.7	22.7	26.1	27.7	183.2
61	Agriculture, Husbandry, Food	21.0	7.5	7.3	9.3	10.1	11.4	10.4	77.1
62	Amusement Devices	8.2	3.4	3.0	3.9	5.6	7.1	8.0	39.1
63	Apparel & Textile	21.7	6.2	6.1	7.2	6.9	9.0	7.5	64.6
64	Earth Working & Well	14.8	5.3	5.5	6.0	5.9	5.9	7.0	50.4
65	Furniture, House Fixtures	19.4	6.7	6.0	9.1	9.9	13.1	13.0	77.2
66	Heating	13.5	5.7	6.7	5.9	4.8	5.3	5.2	47.1
67	Pipes & Joints	9.6	3.2	3.4	3.8	3.7	4.5	4.8	33.1
68	Receptacles	21.5	6.7	6.3	9.4	10.0	11.8	9.4	75.0
69	Miscellaneous-Others	73.2	23.1	22.8	29.0	31.7	38.1	39.0	257.0

Table B.5 Percentage of patents in technological domains in different periods

Technological domain	P0	P1	P2	P3	P4	P5	P6	Total
11 Agriculture, Food, Textiles	2.03	2.45	2.87	2.86	2.62	2.50	2.19	2.41
12 Coating	1.48	1.54	1.63	1.41	1.58	1.46	1.24	1.45
13 Gas	0.55	0.58	0.64	0.49	0.37	0.35	0.35	0.45
14 Organic Compounds	9.94	10.47	8.54	6.62	7.07	5.24	4.18	7.13
19 Miscellaneous-chemical	10.30	11.44	11.55	9.79	10.00	8.21	7.00	9.35
21 Communications	3.20	3.43	3.38	4.43	4.92	6.47	8.00	5.16
22 Computer Hardware & Software	1.10	1.43	2.03	3.15	4.26	7.68	9.49	4.72
23 Computer Peripherals	0.20	0.40	0.61	0.87	1.00	1.69	2.22	1.11
24 Information Storage	1.05	1.12	1.36	1.76	2.24	2.92	3.26	2.09
31 Drugs	1.03	2.92	3.07	3.40	3.71	4.61	3.88	3.16
32 Surgery & Medical Instruments	1.13	1.57	1.99	2.79	3.61	3.88	3.44	2.69
33 Biotechnology	0.34	0.52	0.71	0.92	1.39	2.74	2.27	1.40
39 Miscellaneous-Drug&Med	0.30	0.46	0.58	0.69	0.71	0.77	0.78	0.61
41 Electrical Devices	5.25	3.93	4.29	4.05	3.68	3.75	4.34	4.28
42 Electrical Lighting	1.68	1.41	1.46	1.74	1.66	1.56	1.96	1.68
43 Measuring & Testing	2.81	2.84	3.00	3.15	2.90	2.64	2.89	2.86
44 Nuclear & X-rays	1.33	1.47	1.36	1.90	1.75	1.10	1.35	1.42
45 Power Systems	3.74	3.58	3.76	3.43	3.21	3.50	4.02	3.65
46 Semiconductor Devices	0.72	0.96	1.08	1.69	2.88	3.91	5.99	2.80
49 Miscellaneous-Elec.	1.23	1.33	1.54	1.67	1.55	1.53	1.32	1.42
51 Materials Processing. & Handling	7.46	6.45	5.77	5.22	4.75	3.76	3.20	5.12
52 Metal Working	3.94	3.64	3.26	3.29	2.85	2.12	1.95	2.92
53 Motors, Engines & Parts	3.93	3.99	4.47	4.11	3.46	2.90	2.99	3.56
54 Optics	1.77	2.16	2.15	2.25	2.44	2.72	2.62	2.31
55 Transportation	3.53	3.16	2.94	3.07	2.83	2.47	2.66	2.95
59 Miscellaneous-Mechanical	6.27	5.03	4.90	5.19	4.58	3.83	3.42	4.71
61 Agriculture, Husbandry, Food	2.46	2.41	2.27	2.23	2.04	1.67	1.29	1.98
62 Amusement Devices	0.95	1.09	0.94	0.93	1.13	1.04	0.99	1.01
63 Apparel & Textile	2.54	1.99	1.92	1.71	1.39	1.32	0.92	1.66
64 Earth Working & Well	1.73	1.70	1.72	1.43	1.18	0.87	0.87	1.29
65 Furniture, House Fixtures	2.26	2.14	1.88	2.17	2.01	1.92	1.60	1.98
66 Heating	1.57	1.81	2.11	1.42	0.97	0.78	0.64	1.21
67 Pipes & Joints	1.12	1.02	1.07	0.91	0.75	0.67	0.60	0.85
68 Receptacles	2.51	2.13	1.97	2.24	2.02	1.74	1.16	1.93
69 Miscellaneous-Others	8.55	7.40	7.15	6.95	6.40	5.60	4.81	6.60

Table B.6 Ranking on the basis of share of total patents per period

Technological domain	P1	P2	P3	P4	P5	P6	Total
11 Agriculture, Food, Textiles	17	14	14	15	18	20	17
12 Coating	22	23	24	29	27	27	25
13 Gas	32	32	33	35	35	35	35
14 Organic Compounds	2	2	2	3	5	7	2
19 Miscellaneous-chemical	1	1	1	1	1	3	1
21 Communications	11	10	9	6	3	2	4
22 Computer Hardware & Software	27	25	18	12	2	1	6
23 Computer Peripherals	35	35	34	33	23	19	31
24 Information Storage	28	28	27	22	13	12	19
31 Drugs	29	12	11	10	6	9	11
32 Surgery & Medical Instruments	25	22	19	16	8	10	16
33 Biotechnology	33	33	32	31	15	18	28
39 Miscellaneous-Drug&Med	34	34	35	34	33	32	34
41 Electrical Devices	6	7	7	8	11	6	8
42 Electrical Lighting	20	26	26	23	25	21	23
43 Measuring & Testing	12	13	12	13	17	15	14
44 Nuclear & X-rays	23	24	28	21	29	24	26
45 Power Systems	9	9	8	9	12	8	9
46 Semiconductor Devices	31	31	29	25	7	4	15
49 Miscellaneous-Elec.	24	27	25	26	26	25	27
51 Materials Processing. & Handling	4	4	4	4	10	13	5
52 Metal Working	7	8	10	11	20	22	13
53 Motors, Engines & Parts	8	6	6	7	14	14	10
54 Optics	18	16	16	17	16	17	18
55 Transportation	10	11	13	14	19	16	12
59 Miscellaneous-Mechanical	5	5	5	5	9	11	7
61 Agriculture, Husbandry, Food	15	15	15	19	24	26	21
62 Amusement Devices	30	29	31	30	30	29	32
63 Apparel & Textile	13	19	21	24	28	30	24
64 Earth Working & Well	19	21	23	27	31	31	29
65 Furniture, House Fixtures	16	17	22	20	21	23	20
66 Heating	21	20	17	28	32	33	30
67 Pipes & Joints	26	30	30	32	34	34	33
68 Receptacles	14	18	20	18	22	28	22
69 Miscellaneous-Others	3	3	3	2	4	5	3

Appendix C

Methodology for argument extraction

The method for extracting arguments outlined (Fisher, 1988)[33]:

1. Read through the text to get its sense, circling – thus – all the inference indicators (conclusion indicators, reason indicators, and supposition indicators) as you go.
2. Underline – <u>thus</u> – any clearly indicated conclusion, and bracket – [thus] – any clearly indicated reason. It helps at this stage if one tries to summarize the argument. Mark the distinction between asserted and unasserted propositions, using the ^{u}R for unasserted propositions and R for asserted propositions).
3. Identify what you take to be the main conclusion and mark it C. (There may be more than one.)
4. Starting with C, ask "What immediate reasons are presented in the text for accepting C?" or "Why (in the text) am I asked to believe C?" Mark these reasons R^{n}. Use inference indicators to help answer the question. If the question is hard to answer because the author's intentions are not transparent, then ask the "Assertibility question" (see below). Having done this look to see if the author asserts or clearly assumes these same claims (reasons). If s/he does, it is reasonable as having intended the same argument. If s/he does not, you have no rational way of reconstructing his argument (on the basis of the text alone).
5. For each reason, R, already identified, repeat the process described in step (4) above. Do this until you are left with only the basic reasons and then display the argument(s) in a clear way, say, by means of a diagram.

Assertibility question (in order to decide the appropriate standards): What argument or evidence would justify me in asserting the conclusion? What would I have to know or believe to be justified in accepting it?

[33] This text is copied and slightly adapted from Fisher (1988: 21-22).

Appendix D

Argumentation patterns

1. *Modus ponens*

If postulates '*A*' and 'If *A*, then *B*' are true, it logically follows that '*B*' is also true

$\{A, A \rightarrow B\} \Rightarrow B$

2. *Cut rule*

If postulates 'If *A*, then *B*' and 'If *B*, then *C*' are true, it logically follows that 'If *A*, then *C*' is also true

$\{A \rightarrow B, B \rightarrow C\} \Rightarrow A \rightarrow C$

3. *Contraposition*

If postulate 'If *A*, then *B*' is true, then it logically follows that 'If not *B*, then not *A*' is also true

$\{A \rightarrow B\} \Rightarrow \neg B \rightarrow \neg A$

4. *Modes tollens*

If postulates 'If *A*, then *B*' and 'Not *B*' are true, then it logically follows that 'Not *A*' is also true

$\{A \rightarrow B, \neg B\} \Rightarrow \neg A$

For scientific theory, inference patterns (3) and (4) are problematic because they lead to unwanted (stringent) conditions for theory building (Hannan et al., 2007).

Appendix E

Background assumptions

Background assumption 1

For all A, it is not the case that A is greater than A

$\forall A\ [\neg(A > A)]$

Background assumption 2

For all A and B, if A is greater than B, then it is not the case that B is greater than A

$\forall A,B\ [(A > B) \rightarrow \neg(B > A)]$

Background assumption 3

For all A, B, and C, if A is greater than B, and B is greater than C, then A is greater than C

$\forall A,B,C\ [(A > B) \wedge (B > C) \rightarrow (A > C)]$

Background assumption 4

For all A and B, if A is greater than or equal to B, then either A is equal to B or A is greater than B

$\forall A,B\ [(A \geq B) \rightarrow (A = B) \vee (A > B)]$

Appendix F

Formal proof Theorems Chapter 5

Theorem 5.1

$\mathfrak{P}\ x,x',y,y'\ [C(x,y) \wedge C(x',y') \wedge NO(x,y) > NO(x',y') \ \wedge \forall z,z'\ [y \neq z \wedge y' \neq z' \wedge \sum_z CP(x,z) \geq \sum_{z'} CP(x',z') \wedge \sum_w LP(x,z) \leq \sum_{w'} LP(x',z')] \rightarrow P(x) < P(x')]$

Proof – On the basis of the competitive relations, auxiliary assumption 5.1 gives the relation between the competition and legitimation coefficients, whilst the relative niche overlap can be used to get the relative competencies overlap by using postulate 5.2. Next, on the basis of the relative competencies overlap and the competition coefficients, definitions 5.2 and 5.3 give the relative competitive and legitimative pressures, respectively. Finally, postulate 5.4 can be used to get the relative performance.

Initial condition of Theorem 5.1

$C(x,y) \wedge C(x',y') \wedge NO(x,y) > NO(x',y') \ \wedge \sum_z CP(x,z) \geq \sum_{z'} CP(x',z') \wedge \sum_w LP(x,z) \leq \sum_{w'} LP(x',z')$

Formal proof

A5.1: $C(x,y) \wedge C(x',y') \rightarrow (\gamma_{xy} - \lambda_{xy}) \wedge (\gamma_{x'y'} - \lambda_{x'y'})$

P5.2: $NO(x,y) > NO(x',y') \rightarrow CO(x,y) > CO(x',y')$

D5.2: $CO(x,y) > CO(x',y') \wedge \sum_z CP(x,z) \geq \sum_{z'} CP(x',z') \rightarrow CP(x) > CP(x')$

D5.3: $\sum_w LP(x,z) \leq \sum_{w'} LP(x',z') \rightarrow \ LP(x) \leq LP(x')$

P5.4: $LP(x) \leq LP(x') \wedge CP(x) > CP(x') \rightarrow P(x) < P(x')$

Q.E.D.

Theorem 5.2

$\mathfrak{P}\ x,x',y,y'\ [\neg C(x,y) \wedge \neg C(x',y') \wedge NO(x,y) > NO(x',y') \ \wedge \forall z,z'\ [y \neq z \wedge y' \neq z' \wedge \sum_z CP(x,z) \leq \sum_{z'} CP(x',z') \wedge \sum_w LP(x,z) \geq \sum_{w'} LP(x',z')] \rightarrow P(x) < P(x')]$

Proof – On the basis of the competitive relations, auxiliary assumption 5.1 gives the relation between the competition and legitimation coefficients, whilst the relative niche overlap can be used to get the relative competencies overlap by using postulate 5.2. Next, on the basis of the relative competencies overlap and the competition coefficients, definitions 5.2 and 5.3 give the relative competitive and legitimative pressures, respectively. Finally, postulate 5.5 can be used to get the relative performance.

Initial condition of Theorem 5.2

$\neg C(x,y) \wedge \neg C(x',y') \wedge NO(x,y) > NO(x',y') \wedge \sum_z CP(x,z) \leq \sum_{z'} CP(x',z') \wedge \sum_w LP(x,z) \geq \sum_{w'} LP(x',z')$

Formal proof

A5.1: $\neg C(x,y) \wedge \neg C(x',y') \rightarrow (\gamma_{xy} - \lambda_{xy}) \wedge (\gamma_{x'y'} - \lambda_{x'y'})$

P5.2: $NO(x,y) > NO(x',y') \rightarrow CO(x,y) > CO(x',y')$

D5.2: $\sum_z CP(x,z) \leq \sum_{z'} CP(x',z') \rightarrow CP(x) \leq CP(x')$

D5.3: $CO(x,y) > CO(x',y') \wedge \sum_w LP(x,z) \geq \sum_{w'} LP(x',z') \rightarrow LP(x) > LP(x')$

P5.5: $CP(x) \leq CP(x') \wedge LP(x) > LP(x') \rightarrow P(x) > P(x')$

Q.E.D.

Theorem 5.3

$\mathfrak{P}\, x,x'\, [UC(x) = UC(x') \wedge Q(x) \geq Q(x') \wedge S(x) > S(x') \rightarrow P(x) > P(x')]$

Proof – On the basis of the initial conditions, definition 5.6 can be used to get the relative perceived quality. Next, postulate 5.7 gives the relative ability to mobilize resources, and postulate 5.8 subsequently gives the relative performance.

Initial condition of Theorem 5.3

$UC(x) = UC(x') \wedge Q(x) \geq Q(x') \wedge S(x) > S(x')$

Formal proof

D5.6: $UC(x) = UC(x') \wedge Q(x) \geq Q(x') \wedge S(x) > S(x') \rightarrow PQ(x) > PQ(x')$

P5.7: $PQ(x) > PQ(x') \rightarrow MR(x) > MR(x')$

P5.8: $MR(x) > MR(x') \rightarrow P(x) > P(x')$

Q.E.D.

Theorem 5.4

$\mathfrak{P}\, x,x'\, [UC(x) = UC(x') \wedge Q(x) > Q(x') \vee S(x) \geq S(x') \rightarrow P(x) > P(x')]$

Proof – On the basis of the initial conditions, definition 5.6 can be used to get the relative perceived quality. Next, postulate 5.7 gives the relative ability to mobilize resources, and postulate 5.8 subsequently gives the relative performance.

Initial condition of Theorem 5.4

$UC(x) = UC(x') \wedge Q(x) > Q(x') \vee S(x) \geq S(x')$

Formal proof

D5.6: $UC(x) = UC(x') \wedge Q(x) > Q(x') \vee S(x) \geq S(x') \rightarrow PQ(x) > PQ(x')$

P5.7: $PQ(x) > PQ(x') \rightarrow MR(x) > MR(x')$

P5.8: $MR(x) > MR(x') \rightarrow P(x) > P(x')$

Q.E.D

.

Theorem 5.5

$\mathfrak{P}\ x,x'\ [S(x) > Q(x) \wedge S(x) \geq S(x') \wedge Q(x) \geq Q(x') \wedge UC(x) > UC(x') \rightarrow P(x) > P(x')]$

Proof – According to postulate 5.6, the level of uncertainty is always smaller than zero, and in combination with the initial conditions of theorem 5.5, definition 5.6 can subsequently be used to get the relative perceived quality. Next, postulate 5.7 gives the relative ability to mobilize resources, and postulate 5.8 subsequently gives the relative performance.

Initial condition of Theorem 5.5

$S(x) > Q(x) \wedge S(x) \geq S(x') \wedge Q(x) \geq Q(x') \wedge UC(x) > UC(x')$

Formal proof

P5.6 $UC(x) > 1$

D5.6: $S(x) > Q(x) \wedge S(x) \geq S(x') \wedge Q(x) \geq Q(x') \wedge UC(x) > UC(x') \wedge UC(x) < 1 \rightarrow PQ(x) > PQ(x')$

P5.7: $PQ(x) > PQ(x') \rightarrow MR(x) > MR(x')$

P5.8: $MR(x) > MR(x') \rightarrow P(x) > P(x')$

Q.E.D.

Theorem 5.6

$\mathfrak{P}\ x,x'\ [S(x) < Q(x) \wedge S(x) \leq S(x') \wedge Q(x) \leq Q(x') \wedge UC(x) > UC(x') \rightarrow P(x) < P(x')]$

Proof – According to postulate 5.6, the level of uncertainty is always bigger than zero, and in combination with the initial conditions of theorem 5.5, definition 5.6 can subsequently be used to get the relative perceived quality. Next, postulate 5.7 gives the relative ability to mobilize resources, and postulate 5.8 subsequently gives the relative performance.

Initial condition of Theorem 5.6
$S(x) < Q(x) \wedge S(x) \leq S(x') \wedge Q(x) \leq Q(x') \wedge UC(x) > UC(x')$

Formal proof
P5.6 $UC(x) > 1$
D5.6: $S(x) < Q(x) \wedge S(x) \leq S(x') \wedge Q(x) \leq Q(x') \wedge UC(x) > UC(x') \wedge UC(x) < 1 \rightarrow PQ(x) < PQ(x')$
P5.7: $PQ(x) < PQ(x') \rightarrow MR(x) < MR(x')$
P5.8: $MR(x) < MR(x') \rightarrow P(x) < P(x')$

Q.E.D.

Theorem 5.7
$\mathfrak{P}\ x,x'\ [NO(x) = NO(x') \wedge Q(x) \geq Q(x') \wedge ST(x) > ST(x') \rightarrow P(x) > P(x')]$

Proof – On the basis of the relative niche overlap, auxiliary assumption gives the relative technological novelty, and auxiliary assumption 5.4 can subsequently be used to get the relative technological uncertainty. In combination with the initial conditions of theorem 5.7, definition 5.6 gives the relative perceived quality. Next, postulate 5.7 gives the relative ability to mobilize resources, and postulate 5.8 subsequently gives the relative performance.

Initial condition of Theorem 5.7
$NO(x) = NO(x') \wedge Q(x) \geq Q(x') \wedge ST(x) > ST(x')$

Formal proof
A5.3: $NO(x) = NO(x) \rightarrow N(x) = N(x')$
A5.4: $N(x) = N(x) \rightarrow UC(x) = UC(x')$
D5.6: $UC(x) = UC(x') \wedge Q(x) \geq Q(x') \wedge ST(x) > ST(x') \rightarrow PQ(x) < PQ(x')$
P5.7: $PQ(x) < PQ(x') \rightarrow MR(x) < MR(x')$
P5.8: $MR(x) < MR(x') \rightarrow P(x) < P(x')$

Q.E.D.

Appendix G

Logical symbols, predicates, and functions

Table G.1 Logical symbols, predicates, and functions

Logical constants		
	$\wedge$	conjunction (e.g., A and B)
	$\vee$	disjunction (e.g., A and/or B)
	$\rightarrow$	material implication (e.g., if A, then B)
	$\longleftrightarrow$	material equivalence (e.g., A if and only if B)
	$\neg$	Negation (e.g., not A)
Logical quantifiers		
	$\exists$	classical existential quantifier (e.g., A exists)
	$\forall$	classical universal quantifier (e.g., for all A)
Non-monotonic logical quantifiers		
	$\mathfrak{N}$	non-monotonic 'normally' quantifier (e.g., normally A)
	$\mathfrak{A}$	non-monotonic 'ad-hoc' quantifier (e.g., assumably A)
	$\mathfrak{P}$	non-monotonic 'presumably' quantifier (e.g., presumably A)
Set operators		
	$\cap$	intersection of two sets (i.e., common elements in both sets)
	$\cup$	union of two sets (i.e., all elements from both sets)
	$\lvert \cdot \rvert$	cardinality of a set (i.e., the number of unique elements in the set)
	$\setminus$	set subtraction (i.e., subtract elements of one set from another set)
Predicates		
	$AD(s,t)$	technological system s has alternative design configurations at time t
	$DD(s,t)$	at time t there is a dominant design configuration in technological system s
	$G(s,t)$	technological system s is in the growth stage of development at time t
	$O(x)$	x is an organization
	$T(t)$	t is a point or a period in time
	$TS(s)$	s is a technological system
Functions		
	φ_{st}	technological system s stage switch at time t (1 = seed stage; 0 = growth stage)
	λ_{xyt}	dyadic legitimation coefficient for organizations x and y at time t
	γ_{xyt}	dyadic competition coefficient for organizations x and y at time t
	θ_{xst}	organization x's share of antecedent technology that comes from technological system s at time t
	υ_{xst}	organization x's share of descendant technology that comes from technological system s at time t
	τ_{xst}	organization x's share of technology that comes from technological system s at time t

	CO(*x*,*y*,*s*,*t*)	overlap of organization *x*'s technological competencies by organization *y* in technological system *s* at time *t*
	Cost(*x*,*t*)	organization *x*'s costs at time *t*
	CP(*x*,*t*)	total competitive pressure experienced by organization *x* at time *t*
	D(*x*,*d*,*t*)	organization *x*'s diversity of lineage dimension *d* at time *t*
	LP(*x*,*t*)	total legitimative pressure experienced by organization *x* at time *t*
	M(*x*,*d*,*t*)	organization *x*'s diversity multiplier for lineage dimension *d* at time *t*
	MR(*x*,*t*)	organization *x*'s ability to mobilize resources at time *t*
	MR(*x*,*s*,*t*)	organization *x*'s ability to mobilize resources from system *s* at time *t*
	NC(*x*,*y*,*s*,*t*)	non-overlap of organization *x*'s technological competencies by organization *y* in technological system *s* at time *t*
	NN(*x*,*y*,*s*,*t*)	non-overlap of organization *x*'s technological niche by organization *y* in technological system *s* at time *t*
	NO(*x*,*y*,*s*,*t*)	overlap of organization *x*'s technological niche by organization *y* in technological system *s* at time *t*
	NT(*x*,*y*,*s*,*t*)	non-overlap of organization *x*'s technological antecedents by organization *y* in technological system *s* at time *t*
	Opp(*x*,*t*)	organization *x*'s opportunities at time *t*
	P(*x*,*t*)	performance of organization *x* at time *t*
	PQ(*x*,*s*,*t*)	the perceived technological quality of organization *x* in technological system *s* at time *t*
	Q(*x*,*s*,*t*)	technological quality of organization *x* in technological system *s* at time *t*
	S(*x*,*s*,*t*)	technological status of organization *x* in technological system *s* at time *t*
	TA(*x*,*y*,*s*,*t*)	overlap of organization *x*'s technological antecedents by organization *y* in technological system *s* at time *t*
	T(*s*,*t*)	the technological opportunities in system *s* at time *t*
	TO(*x*,*t*)	the technological opportunities for organization *x* at time *t*
	UC(*s*,*t*)	the uncertainty technological system *s* at time *t*

Appendix H

Theorem development crowding argument

Table H.1 Partial modified truth table of crowding argument

Theorems	$TS(s)$	NO ? NO'	NN ? NN'	λ ? λ'	γ ? γ'	LP ? LP'	CP ? CP'	P ? P'
T6.1	¬G	>	≤	≥	≤	≥	≤	>
T6.2	¬G	≥	≤	>	≤	≥	≤	>
T6.3	G	>	≤	≤	≥	≤	≥	<
T6.4	G	≥	≤	≤	>	≤	≥	<
T6.5	¬G	≤	>	≤	≥	≤	≥	<
T6.6	¬G	≤	≥	≤	>	≤	≥	<
T6.7	G	≤	>	≥	≤	≥	≤	>
T6.8	G	≤	≥	>	≤	≥	≤	>

For columns 3 to 9, statements are formed by replacing "?" by the appropriate symbol in the row to make a complete (partial) statement; we have excluded the scenarios for which it is impossible to determine whether the performance of one or the other organization is higher or lower.

Table H.2 Legend

Symbol	**Meaning**
$\neg G$	$\neg G(s,t) \wedge \neg G(s,t)$
G	$G(s,t) \wedge G(s,t)$
NO	$NO(x,y,s,t)$
NO'	$NO(x',y',s,t')$
NN	$NN(x,y,s,t)$
NN'	$NN(x',y',s,t')$
λ	λ_{xyt}
λ'	$\lambda_{x'y't'}$
γ	γ_{xyt}
γ'	$\gamma_{x'y't'}$
LP	$LP(x,y,t)$
LP'	$LP(x',y',t')$
CP	$CP(x,y,t)$
CP'	$CP(x',y',t')$
P	$P(x,y,t)$
P'	$P(x',y',t')$

Appendix I

Theorem development status argument

Table I.1 Partial modified truth table of status argument

Theorems	**Additional**	***UC*?*UC′***	***Q*?*Q′***	***S*?*S′***	***Q*?*S***	***P*?*P′***
T6.9		=	>	≥		>
T6.10		=	≥	>		>
T6.11		<	≤	≤	<	<
T6.12		>	≤	≤	>	<
T6.13	G(s,t) ∧ t' > t	>†	≤	≤	>	<
T6.14	¬G(s,t) ∧ G(s,t')	>†	≤	≤	>	<
T6.15	G(s,t') ∧ t > t'	<†	≤	≤	<	<
T6.16	G(s,t) ∧ ¬G(s,t')	<†	≤	≤	<	<

For columns 3 to 7, statements are formed by replacing "?" by the appropriate symbol in the row to make a complete (partial) statement; we have excluded the scenarios for which it is impossible to determine whether the performance of one or the other organization is higher or lower. † This condition is the result of the "Additional" condition and not explicitly included in the theorem.

Table I.2 Legend

Symbol	**Meaning**
Q	$Q(x,s,t)$
Q'	$Q(x',s,t')$
UC	$UC(s,t)$
UC'	$UC(s,t')$
S	$S(x,s,t)$
S'	$S(x',s,t')$
P	$P(x,y,t)$
P'	$P(x',y',t')$

Appendix J

Formal proof theorems Chapter 6

Theorem 6.1

$\mathfrak{P}\ x,x',y,y',s,t,t'\ [\neg G(s,t) \wedge \neg G(s,t') \wedge NO(x,y,s,t) > NO(x',y',s,t') \wedge NN(x,y,s,t) \leq NN(x',y',s,t') \wedge \lambda_{xyt} \geq \lambda_{x'y't'} \wedge \gamma_{xyt} \leq \gamma_{x'y't'} \wedge \forall\ z,z'\ [x \neq y \wedge y \neq z \wedge y' \neq z' \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t')] \rightarrow P(x,t) > P(x',t')]$

Proof – First, auxiliary assumption 6.1 gives us the value of the switch of the system's stage of technological development. Second, on the basis of the relative niche overlap, postulate 6.6 gives the relative competency overlap, and in combination with the relative legitimation coefficients and the system's switch, we can use definition 6.5 to determine the relative dyadic legitimative pressure as a result of organization *y*. Auxiliary assumption 6.2 can subsequently be used to aggregate the relative dyadic legitimative pressures to the organizational level. Third, on the basis of the relative niche non-overlap, postulate 6.8 gives the relative non-competency overlap, and in combination with the relative competition coefficients and the system's switch, we can use definition 6.6 to determine the relative dyadic competitive pressure as a result of organization *y*. Auxiliary assumption 6.3 can subsequently be used to aggregate the relative dyadic legitimative pressures to the organizational level. Fourth and finally, on the basis of the relative legitimative and competitive pressure, postulate 6.12 gives the relative performance.

The initial condition of Theorem 6.1

$\neg G(s,t) \wedge \neg G(s,t') \wedge NO(x,y,s,t) > NO(x',y',s,t') \wedge NN(x,y,s,t) \leq NN(x',y',s,t') \wedge \lambda_{xyt} \geq \lambda_{x'y't'} \wedge \gamma_{xyt} \leq \gamma_{x'y't'} \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t')$

Formal proof

A6.1: $(\neg G(s,t) \rightarrow \varphi_{st} = 1) \wedge (\neg G(s,t') \rightarrow \varphi_{st'} = 1)$

P6.6: $NO(x,y,s,t) > NO(x',y',s,t') \rightarrow CO(x,y,s,t) > CO(x',y',s,t')$

D6.5: $\lambda_{xyt} \geq \lambda_{x'y't'} \wedge CO(x,y,s,t) > CO(x',y',s,t') \wedge \varphi_{st} = 1 \wedge \varphi_{st'} = 1 \rightarrow LP(x,y,t) > LP(x',y',t')$

A6.2: $LP(x,y,t) > LP(x',y',t') \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \rightarrow LP(x,t) > LP(x',t')$

P6.8: $NN(x,y,s,t) \leq NN(x',y',s,t') \rightarrow NC(x,y,s,t) \leq NC(x',y',s,t')$

D6.6: $\gamma_{xyt} \leq \gamma_{x'y't'} \wedge NC(x,y,s,t) \leq NC(x',y',s,t') \rightarrow CP(x,y,t) \leq CP(x',y',t')$

A6.3: $CP(x,y,t) \leq CP(x',y',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t') \rightarrow CP(x,t) \leq CP(x',t')$

P6.12: $LP(x,t) > LP(x',t') \wedge CP(x,t) \leq CP(x',t') \rightarrow P(x,t) > P(x',t')$

Q.E.D.

Theorem 6.2

$\mathfrak{P}\, x,x',y,y',s,t,t'\; [\neg G(s,t) \wedge \neg G(s,t') \wedge NO(x,y,s,t) \geq NO(x',y',s,t') \wedge NN(x,y,s,t)$
$\leq NN(x',y',s,t') \wedge \lambda_{xyt} > \lambda_{x'y't'} \wedge \gamma_{xyt} \leq \gamma_{x'y't'} \wedge \forall\, z,z'\; [x \neq y \;\wedge y \neq z \;\wedge y' \neq z' \;\wedge \sum_z LP(x,z,t) \geq$
$\sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t')] \rightarrow P(x,t) > P(x',t')]$

Proof – First, auxiliary assumption 6.1 gives us the value of the switch of the system's stage of technological development. Second, on the basis of the relative niche overlap, postulate 6.6 gives the relative competency overlap, and in combination with the relative legitimation coefficients and the system's switch, we can use definition 6.5 to determine the relative dyadic legitimative pressure as a result of organization *y*. Auxiliary assumption 6.2 can subsequently be used to aggregate the relative dyadic legitimative pressures to the organizational level. Third, on the basis of the relative niche non-overlap, postulate 6.8 gives the relative non-competency overlap, and in combination with the relative competition coefficients and the system's switch, we can use definition 6.6 to determine the relative dyadic competitive as a result of organization *y*. Auxiliary assumption 6.3 can subsequently be used to aggregate the relative dyadic legitimative pressures to the organizational level. Fourth and finally, on the basis of the relative legitimative and competitive pressure, postulate 6.12 gives the relative performance.

The initial condition of Theorem 6.2

$\neg G(s,t) \wedge \neg G(s,t') \wedge NO(x,y,s,t) \geq NO(x',y',s,t') \wedge NN(x,y,s,t) \leq NN(x',y',s,t') \wedge \lambda_{xyt} > \lambda_{x'y't'}$
$\wedge\, \gamma_{xyt} \leq \gamma_{x'y't'} \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t')$

Formal proof

A6.1: $(\neg G(s,t) \rightarrow \varphi_{st} = 1) \wedge (\neg G(s,t') \rightarrow \varphi_{st'} = 1)$
P6.6: $NO(x,y,s,t) \geq NO(x',y',s,t') \rightarrow CO(x,y,s,t) \geq CO(x',y',s,t')$
D6.5: $\lambda_{xyt} > \lambda_{x'y't'} \wedge CO(x,y,s,t) \geq CO(x',y',s,t') \wedge \varphi_{st} = 1 \wedge \varphi_{st'} = 1 \rightarrow LP(x,y,t) > LP(x',y',t')$
A6.2: $LP(x,y,t) > LP(x',y',t') \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \rightarrow LP(x,t) > LP(x',t')$
P6.8: $NN(x,y,s,t) \leq NN(x',y',s,t') \rightarrow NC(x,y,s,t) \leq NC(x',y',s,t')$
D6.6: $\gamma_{xyt} \leq \gamma_{x'y't'} \wedge NC(x,y,s,t) \leq NC(x',y',s,t') \wedge \varphi_{st} = 1 \wedge \varphi_{st'} = 1 \rightarrow CP(x,y,t) \leq CP(x',y',t')$
A6.3: $CP(x,y,t) \leq CP(x',y',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t') \rightarrow CP(x,t) \leq CP(x',t')$
P6.12: $LP(x,t) > LP(x',t') \wedge CP(x,t) \leq CP(x',t') \rightarrow P(x,t) > P(x',t')$

Q.E.D.

Theorem 6.3

$\mathfrak{P}\, x,x',y,y',d,t,t'\ [G(s,t) \wedge G(s,t') \wedge NO(x,y,s,t) > NO(x',y',s,t') \wedge NN(x,y,s,t) \leq NN(x',y',s,t') \wedge \lambda_{xyt} \leq \lambda_{x'y't'} \wedge \gamma_{xyt} \geq \gamma_{x'y't'} \wedge \forall\, z,z'\ [x \neq y \wedge y \neq z \wedge y' \neq z' \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t')] \rightarrow P(x,t) < P(x',t')]$

Proof – First, auxiliary assumption 6.1 gives us the value of the switch of the system's stage of technological development. Second, on the basis of the relative niche overlap, postulate 6.6 gives the relative competency overlap, and in combination with the relative competition coefficients and the system's switch, we can use definition 6.6 to determine the relative dyadic competitive pressure as a result of organization *y*. Auxiliary assumption 6.3 can subsequently be used to aggregate the relative dyadic competitive pressures to the organizational level. Third, on the basis of the relative niche non-overlap, postulate 6.8 gives the relative non-competency overlap, and in combination with the relative legitimation coefficients and the system's switch, we can use definition 6.5 to determine the relative dyadic legitimative pressure as a result of organization *y*. Auxiliary assumption 6.2 can subsequently be used to aggregate the relative dyadic legitimative pressures to the organizational level. Fourth and finally, on the basis of the relative legitimative and competitive pressure, postulate 6.11 gives the relative performance.

The initial condition of Theorem 6.3

$G(s,t) \wedge G(s,t') \wedge NO(x,y,s,t) > NO(x',y',s,t') \wedge NN(x,y,s,t) \leq NN(x',y',s,t') \wedge \lambda_{xyt} \leq \lambda_{x'y't'} \wedge \gamma_{xyt} \geq \gamma_{x'y't'} \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t')$

Formal proof

A6.1: $(G(s,t) \rightarrow \varphi_{st} = 0) \wedge (G(s,t') \rightarrow \varphi_{st'} = 0)$

P6.6: $NO(x,y,s,t) > NO(x',y',s,t') \rightarrow CO(x,y,s,t) > CO(x',y',s,t')$

D6.6: $\gamma_{xyt} \geq \gamma_{x'y't'} \wedge CO(x,y,s,t) > CO(x',y',s,t') \wedge \varphi_{st} = 0 \wedge \varphi_{st'} = 0 \rightarrow CP(x,y,t) > CP(x',y',t')$

A6.3: $CP(x,y,t) > CP(x',y',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t') \rightarrow CP(x,t) > CP(x',t')$

P6.8: $NN(x,y,s,t) \leq NN(x',y',s,t') \rightarrow NC(x,y,s,t) \leq NC(x',y',s,t')$

D6.5: $\lambda_{xyt} \leq \lambda_{x'y't'} \wedge NC(x,y,s,t) \leq NC(x',y',s,t') \wedge \varphi_{st} = 0 \wedge \varphi_{st'} = 0 \rightarrow LP(x,y,t) \leq LP(x',y',t')$

A6.2: $LP(x,y,t) \leq LP(x',y',t') \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \rightarrow LP(x,t) \leq LP(x',t')$

P6.11: $LP(x,t) \leq LP(x',t') \wedge CP(x,t) > CP(x',t') \rightarrow P(x,t) < P(x',t')$

Q.E.D.

Theorem 6.4

$\mathfrak{P}\ x,x',y,y',s,t,t'\ [G(s,t) \wedge G(s,t') \wedge NO(x,y,s,t) \geq NO(x',y',s,t') \wedge NN(x,y,s,t) \leq NN(x',y',s,t') \wedge \lambda_{xyt} \leq \lambda_{x'y't'} \wedge \gamma_{xyt} > \gamma_{x'y't'} \wedge \forall\ z,z'\ [x \neq y \ \wedge y \neq z \ \wedge y' \neq z' \ \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t')] \rightarrow P(x,t) < P(x',t')]$

Proof – First, auxiliary assumption 6.1 gives us the value of the switch of the system's stage of technological development. Second, on the basis of the relative niche overlap, postulate 6.6 gives the relative competency overlap, and in combination with the relative competition coefficients and the system's switch, we can use definition 6.6 to determine the relative dyadic competitive pressure as a result of organization *y*. Auxiliary assumption 6.3 can subsequently be used to aggregate the relative dyadic competitive pressures to the organizational level. Third, on the basis of the relative niche non-overlap, postulate 6.8 gives the relative non-competency overlap, and in combination with the relative legitimation coefficients and the system's switch, we can use definition 6.5 to determine the relative dyadic legitimative pressure as a result of organization *y*. Auxiliary assumption 6.2 can subsequently be used to aggregate the relative dyadic legitimative pressures to the organizational level. Fourth and finally, on the basis of the relative legitimative and competitive pressure, postulate 6.11 gives the relative performance.

The initial condition of Theorem 6.4

$G(s,t) \wedge G(s,t') \wedge NO(x,y,s,t) \geq NO(x',y',s,t') \wedge NN(x,y,s,t) \leq NN(x',y',s,t') \wedge \lambda_{xyt} \leq \lambda_{x'y't'} \wedge \gamma_{xyt} > \gamma_{x'y't'} \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t')$

Formal proof

A6.1: $(G(s,t) \rightarrow \varphi_{st} = 0) \wedge (G(s,t') \rightarrow \varphi_{st'} = 0)$

P6.6: $NO(x,y,s,t) \geq NO(x',y',s,t') \rightarrow CO(x,y,s,t) \geq CO(x',y',s,t')$

D6.6: $\gamma_{xyt} > \gamma_{x'y't'} \wedge CO(x,y,s,t) \geq CO(x',y',s,t') \wedge \varphi_{st} = 0 \wedge \varphi_{st'} = 0 \rightarrow CP(x,y,t) > CP(x',y',t')$

A6.3: $CP(x,y,t) > CP(x',y',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t') \rightarrow CP(x,t) > CP(x',t')$

P6.8: $NN(x,y,s,t) \leq NN(x',y',s,t') \rightarrow NC(x,y,s,t) \leq NC(x',y',s,t')$

D6.5: $\lambda_{xyt} \leq \lambda_{x'y't'} \wedge NC(x,y,s,t) \leq NC(x',y',s,t') \wedge \varphi_{st} = 0 \wedge \varphi_{st'} = 0 \rightarrow LP(x,y,t) \leq LP(x',y',t')$

A6.2: $LP(x,y,t) \leq LP(x',y',t') \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \rightarrow LP(x,t) \leq LP(x',t')$

P6.11: $LP(x,t) \leq LP(x',t') \wedge CP(x,t) > CP(x',t') \rightarrow P(x,t) < P(x',t')$

Q.E.D.

Theorem 6.5

$\mathfrak{P}\ x,x',y,y',s,t,t'\ [\neg G(s,t) \wedge \neg G(s,t') \wedge NO(x,y,s,t) \leq NO(x',y',s,t') \wedge NN(x,y,s,t) > NN(x',y',s,t') \wedge \lambda_{xyt} \leq \lambda_{x'y't'} \wedge \gamma_{xyt} \geq \gamma_{x'y't'}\ \forall\ z,z'\ [x \neq y \wedge y \neq z \wedge y' \neq z' \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t')] \rightarrow P(x,t) < P(x',t')]$

Proof – First, auxiliary assumption 6.1 gives us the value of the switch of the system's stage of technological development. Second, on the basis of the relative niche overlap, postulate 6.6 gives the relative competency overlap, and in combination with the relative legitimation coefficients and the system's switch, we can use definition 6.5 to determine the relative dyadic legitimative pressure as a result of organization *y*. Auxiliary assumption 6.2 can subsequently be used to aggregate the relative dyadic legitimative pressures to the organizational level. Third, on the basis of the relative niche non-overlap, postulate 6.8 gives the relative non-competency overlap, and in combination with the relative competition coefficients and the system's switch, we can use definition 6.6 to determine the relative dyadic competitive pressure as a result of organization *y*. Auxiliary assumption 6.3 can subsequently be used to aggregate the relative dyadic competitive pressures to the organizational level. Fourth and finally, on the basis of the relative legitimative and competitive pressure, postulate 6.11 gives the relative performance.

The initial condition of Theorem 6.5

$\neg G(s,t) \wedge \neg G(s,t') \wedge NO(x,y,s,t) \leq NO(x',y',s,t') \wedge NN(x,y,s,t) > NN(x',y',s,t') \wedge \lambda_{xyt} \leq \lambda_{x'y't'} \wedge \gamma_{xyt} \geq \gamma_{x'y't'} \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t')$

Formal proof

A6.1: $(G(s,t) \rightarrow \varphi_{st} = 1) \wedge (G(s,t') \rightarrow \varphi_{st'} = 1)$

P6.6: $NO(x,y,s,t) \leq NO(x',y',s,t') \rightarrow CO(x,y,s,t) \leq CO(x',y',s,t')$

D6.5: $\lambda_{xyt} \leq \lambda_{x'y't'} \wedge CO(x,y,s,t) \leq CO(x',y',s,t') \wedge \varphi_{st} = 1 \wedge \varphi_{st'} = 1 \rightarrow LP(x,y,t) \leq LP(x',y',t')$

A6.2: $LP(x,y,t) \leq LP(x',y',t') \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \rightarrow LP(x,t) \leq LP(x',t')$

P6.8: $NN(x,y,s,t) > NN(x',y',s,t') \rightarrow NC(x,y,s,t) > NC(x',y',s,t')$

D6.6: $\gamma_{xyt} \geq \gamma_{x'y't'} \wedge NC(x,y,s,t) > NC(x',y',s,t') \wedge \varphi_{st} = 1 \wedge \varphi_{st'} = 1 \rightarrow CP(x,y,t) > CP(x',y',t')$

A6.3: $CP(x,y,t) > CP(x',y',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t') \rightarrow CP(x,t) > CP(x',t')$

P6.11: $LP(x,t) \leq LP(x',t') \wedge CP(x,t) > CP(x',t') \rightarrow P(x,t) < P(x',t')$

Q.E.D.

Theorem 6.6

$\mathfrak{P}\ x,x',y,y',s,t,t'\ [\neg G(s,t) \wedge \neg G(s,t') \wedge NO(x,y,s,t) \leq NO(x',y',s,t') \wedge NN(x,y,s,t) \geq NN(x',y',s,t') \wedge \lambda_{xyt} \leq \lambda_{x'y't'} \wedge \gamma_{xyt} > \gamma_{x'y't'}\ \forall\ z,z'\ [x \neq y \wedge y \neq z \wedge y' \neq z' \wedge LP(x,z,t) \leq LP(x',z',t') \wedge CP(x,z,t) \geq CP(x',z',t')] \rightarrow P(x,t) < P(x',t')]$

Proof – First, auxiliary assumption 6.1 gives us the value of the switch of the system's stage of technological development. Second, on the basis of the relative niche overlap, postulate 6.6 gives the relative competency overlap, and in combination with the relative legitimation coefficients and the system's switch, we can use definition 6.5 to determine the relative dyadic legitimative pressure as a result of organization *y*. Auxiliary assumption 6.2 can subsequently be used to aggregate the relative dyadic legitimative pressures to the organizational level. Third, on the basis of the relative niche non-overlap, postulate 6.8 gives the relative non-competency overlap, and in combination with the relative competition coefficients and the system's switch, we can use definition 6.6 to determine the relative dyadic competitive pressure as a result of organization *y*. Auxiliary assumption 6.3 can subsequently be used to aggregate the relative dyadic competitive pressures to the organizational level. Fourth and finally, on the basis of the relative legitimative and competitive pressure, postulate 6.11 gives the relative performance.

The initial condition of Theorem 6.6

$\neg G(s,t) \wedge \neg G(s,t') \wedge NO(x,y,s,t) \leq NO(x',y',s,t') \wedge NN(x,y,s,t) \geq NN(x',y',s,t') \wedge \lambda_{xyt} \leq \lambda_{x'y't'} \wedge \gamma_{xyt} > \gamma_{x'y't'} \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t')$

Formal proof

***A6.1**:* $(G(s,t) \rightarrow \varphi_{st} = 1) \wedge (G(s,t') \rightarrow \varphi_{st'} = 1)$

***P6.6**:* $NO(x,y,s,t) \leq NO(x',y',s,t') \rightarrow CO(x,y,s,t) \leq CO(x',y',s,t')$

***D6.5**:* $\lambda_{xyt} \leq \lambda_{x'y't'} \wedge CO(x,y,s,t) \leq CO(x',y',s,t') \wedge \varphi_{st} = 1 \wedge \varphi_{st'} = 1 \rightarrow LP(x,y,t) \leq LP(x',y',t')$

***A6.2**:* $LP(x,y,t) \leq LP(x',y',t') \wedge \sum_z LP(x,z,t) \leq \sum_z LP(x',z',t') \rightarrow LP(x,t) \leq LP(x',t')$

***P6.8**:* $NN(x,y,s,t) \geq NN(x',y',s,t') \rightarrow NC(x,y,s,t) \geq NC(x',y',s,t')$

***D6.6**:* $\gamma_{xyt} > \gamma_{x'y't'} \wedge NC(x,y,s,t) \geq NC(x',y',s,t') \wedge \varphi_{st} = 1 \wedge \varphi_{st'} = 1 \rightarrow CP(x,y,t) > CP(x',y',t')$

***A6.3**:* $CP(x,y,t) > CP(x',y',t') \wedge \sum_z CP(x,z,t) \geq \sum_z CP(x',z',t') \rightarrow CP(x,t) > CP(x',t')$

***P6.11**:* $LP(x,t) \leq LP(x',t') \wedge CP(x,t) > CP(x',t') \rightarrow P(x,t) < P(x',t')$

Q.E.D.

Theorem 6.7

$\mathfrak{P}\ x,x',y,y',s,t,t'\ [G(s,t) \wedge G(s,t') \wedge NO(x,y,s,t) \leq NO(x',y',s,t') \wedge NN(x,y,s,t) > NN(x',y',s,t') \wedge \lambda_{xyt} \geq \lambda_{x'y't'} \wedge \gamma_{xyt} \leq \gamma_{x'y't'} \wedge \forall\ z,z'\ [x \neq y\ \wedge y \neq z\ \wedge y' \neq z'\ \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t')] \rightarrow P(x,t) > P(x',t')]$

Proof – First, auxiliary assumption 6.1 gives us the value of the switch of the system's stage of technological development. Second, on the basis of the relative niche overlap, postulate 6.6 gives the relative competency overlap, and in combination with the relative competition coefficients and the system's switch, we can use definition 6.6 to determine the relative dyadic competitive pressure as a result of organization *y*. Auxiliary assumption 6.3 can subsequently be used to aggregate the relative dyadic copetitive pressures to the organizational level. Third, on the basis of the relative niche non-overlap, postulate 6.8 gives the relative non-competency overlap, and in combination with the relative legitimation coefficients and the system's switch, we can use definition 6.5 to determine the relative dyadic legitimative pressure as a result of organization *y*. Auxiliary assumption 6.2 can subsequently be used to aggregate the relative dyadic legitimative pressures to the organizational level. Fourth and finally, on the basis of the relative legitimative and competitive pressure, postulate 6.12 gives the relative performance.

The initial condition of Theorem 6.7

$G(s,t) \wedge G(s,t') \wedge NO(x,y,s,t) \leq NO(x',y',s,t') \wedge NN(x,y,s,t) > NN(x',y',s,t') \wedge \lambda_{xyt} \geq \lambda_{x'y't'} \wedge \gamma_{xyt} \leq \gamma_{x'y't'} \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t')$

Formal proof

A6.1: $(G(s,t) \rightarrow \varphi_{st} = 0) \wedge (G(s,t') \rightarrow \varphi_{st'} = 0)$

P6.6: $NO(x,y,s,t) \leq NO(x',y',s,t') \rightarrow CO(x,y,s,t) \leq CO(x',y',s,t')$

D6.6: $\gamma_{xyt} \leq \gamma_{x'y't'} \wedge CO(x,y,s,t) \leq CO(x',y',s,t') \wedge \varphi_{st} = 0 \wedge \varphi_{st'} = 0 \rightarrow CP(x,y,t) \leq CP(x',y',t')$

A6.3: $CP(x,y,t) \leq CP(x',y',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t') \rightarrow CP(x,t) \leq CP(x',t')$

P6.8: $NN(x,y,s,t) > NN(x',y',s,t') \rightarrow NC(x,y,s,t) > NC(x',y',s,t')$

D6.5: $\lambda_{xyt} \geq \lambda_{x'y't'} \wedge NC(x,y,s,t) > NC(x',y',s,t') \wedge \varphi_{st} = 0 \wedge \varphi_{st'} = 0 \rightarrow LP(x,y,t) > LP(x',y',t')$

A6.2: $LP(x,y,t) > LP(x',y',t') \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \rightarrow LP(x,t) > LP(x',t')$

P6.12: $LP(x,t) > LP(x',t') \leq CP(x,t) > CP(x',t') \rightarrow P(x,t) > P(x',t')$

Q.E.D.

Theorem 6.8

$\mathfrak{P}\ x,x',y,y',s,t,t'\ [G(s,t) \wedge G(s,t') \wedge NO(x,y,s,t) \leq NO(x',y',s,t') \wedge NN(x,y,s,t) \geq NN(x',y',s,t') \wedge \lambda_{xyt} > \lambda_{x'y't'} \wedge \gamma_{xyt} \leq \gamma_{x'y't'} \wedge \forall\ z,z'\ [x \neq y \wedge y \neq z \wedge y' \neq z' \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t')] \rightarrow P(x,t) > P(x',t')]$

Proof – First, auxiliary assumption 6.1 gives us the value of the switch of the system's stage of technological development. Second, on the basis of the relative niche overlap, postulate 6.6 gives the relative competency overlap, and in combination with the relative competition coefficients and the system's switch, we can use definition 6.6 to determine the relative dyadic competitive pressure as a result of organization *y*. Auxiliary assumption 6.3 can subsequently be used to aggregate the relative dyadic copetitive pressures to the organizational level. Third, on the basis of the relative niche non-overlap, postulate 6.8 gives the relative non-competency overlap, and in combination with the relative legitimation coefficients and the system's switch, we can use definition 6.5 to determine the relative dyadic legitimative pressure as a result of organization *y*. Auxiliary assumption 6.2 can subsequently be used to aggregate the relative dyadic legitimative pressures to the organizational level. Fourth and finally, on the basis of the relative legitimative and competitive pressure, postulate 6.12 gives the relative performance.

The initial condition of Theorem 6.7

$G(s,t) \wedge G(s,t') \wedge NO(x,y,s,t) \leq NO(x',y',s,t') \wedge NN(x,y,s,t) \geq NN(x',y',s,t') \wedge \lambda_{xyt} > \lambda_{x'y't'} \wedge \gamma_{xyt} \leq \gamma_{x'y't'} \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t')$

Formal proof

***A6.1**:* $(G(s,t) \rightarrow \varphi_{st} = 0) \wedge (G(s,t') \rightarrow \varphi_{st'} = 0)$

***P6.6**:* $NO(x,y,s,t) \leq NO(x',y',s,t') \rightarrow CO(x,y,s,t) \leq CO(x',y',s,t')$

***D6.6**:* $\gamma_{xyt} \leq \gamma_{x'y't'} \wedge CO(x,y,s,t) \leq CO(x',y',s,t') \wedge \varphi_{st} = 0 \wedge \varphi_{st'} = 0 \rightarrow CP(x,y,t) \leq CP(x',y',t')$

***A6.3**:* $CP(x,y,t) \leq CP(x',y',t') \wedge \sum_z CP(x,z,t) \leq \sum_z CP(x',z',t') \rightarrow CP(x,t) \leq CP(x',t')$

***P6.8**:* $NN(x,y,s,t) \geq NN(x',y',s,t') \rightarrow NC(x,y,s,t) \geq NC(x',y',s,t')$

***D6.5**:* $\lambda_{xyt} > \lambda_{x'y't'} \wedge NC(x,y,s,t) \geq NC(x',y',s,t') \wedge \varphi_{st} = 0 \wedge \varphi_{st'} = 0 \rightarrow LP(x,y,t) > LP(x',y',t')$

***A6.2**:* $LP(x,y,t) > LP(x',y',t') \wedge \sum_z LP(x,z,t) \geq \sum_z LP(x',z',t') \rightarrow LP(x,t) > LP(x',t')$

***P6.12**:* $LP(x,t) > LP(x',t') \leq CP(x,t) > CP(x',t') \rightarrow P(x,t) > P(x',t')$

Q.E.D.

Theorem 6.9

$\mathfrak{P}\ x,x',s,t,t'\ [UC(s,t) = UC(s,t') \wedge Q(x,s,t) > Q(x',s,t') \wedge S(x,s,t) \geq S(x,s,t') \wedge \forall\ z\ [s \neq z \wedge \sum_z MR(x,z,t) \geq \sum_z MR(x',z,t')] \rightarrow P(x,t) > P(x',t')]$

Proof – On the basis of the relative uncertainty, quality, and status, definition 6.9 can be used to determine the relative perceived quality within a technological system. Next, on the basis of this relative perceived quality we use postulate 6.14 to get the relative ability to mobilize resources with that technological system, and in combination with the ability to mobilize resources in the alternative technological domains, we can use definition 6.10 to aggregate the ability to mobilize resources to the organizational level, while postulate 6.15 can subsequently be employed to determine the relative performance.

Initial condition Theorem 6.9

$UC(s,t) = UC(s,t') \wedge Q(x,s,t) > Q(x',s,t') \wedge S(x,s,t) \geq S(x,s,t') \wedge \sum_z MR(x,z,t) \geq \sum_z MR(x',z,t')$

Formal proof

D6.9: $UC(s,t) = UC(s,t') \wedge Q(x,s,t) > Q(x',s,t') \wedge S(x,s,t) \geq S(x,s,t') \rightarrow PQ(x,s,t) > PQ(x',s,t')$

P6.14: $PQ(x,s,t) > PQ(x,s,t') \rightarrow MR(x,s,t) > MR(x',s,t')$

D6.10: $MR(x,s,t) > MR(x',s,t') \wedge \sum_z MR(x,z,t) \geq \sum_z MR(x',z,t') \rightarrow MR(x,t) > MR(x',t')$

P6.15: $MR(x,t) > MR(x',t') \rightarrow P(x,t) > P(x',t')$

Q.E.D.

Theorem 6.10

$\mathfrak{P}\ x,x',s,t,t'\ [UC(s,t) = UC(s,t') \wedge Q(x,s,t) \geq Q(x',s,t') \wedge S(x,s,t) > S(x',s,t') \wedge \forall\ z\ [s \neq z \wedge \sum_z MR(x,z,t) \geq \sum_z MR(x',z,t')] \rightarrow P(x,t) > P(x',t')]$

Proof – On the basis of the relative uncertainty, quality, and status, definition 6.9 can be used to determine the relative perceived quality within a technological system. Next, on the basis of this relative perceived quality we use postulate 6.14 to get the relative ability to mobilize resources with that technological system, and in combination with the ability to mobilize resources in the alternative technological domains, we can use definition 6.10 to aggregate the ability to mobilize resources to the organizational level, while postulate 6.15 can subsequently be employed to determine the relative performance.

Initial condition Theorem 6.10

$UC(s,t) = UC(s,t') \wedge Q(x,s,t) \geq Q(x',s,t') \wedge S(x,s,t) > S(x,s,t') \wedge \sum_z MR(x,z,t) \geq \sum_z MR(x',z,t')$

Formal proof

D6.9: $UC(s,t) = UC(s,t') \wedge Q(x,s,t) \geq Q(x',s,t') \wedge S(x,s,t) > S(x,s,t') \rightarrow PQ(x,s,t) > PQ(x',s,t')$

P6.14: $PQ(x,s,t) > PQ(x,s,t') \rightarrow MR(x,s,t) > MR(x',s,t')$

D6.10: $MR(x,s,t) > MR(x',s,t') \wedge \sum_z MR(x,z,t) \geq \sum_z MR(x',z,t') \rightarrow MR(x,t) > MR(x',t')$

P6.15: $MR(x,t) > MR(x',t') \rightarrow P(x,t) > P(x',t')$

Q.E.D.

Theorem 6.11

$\mathfrak{P}\; x,x',s,t,t' \;[UC(s,t) < UC(s,t') \wedge Q(x,s,t) \leq Q(x',s,t') \wedge S(x,s,t) \leq S(x',s,t') \wedge$

$Q(x,s,t) < S(x,s,t) \wedge \forall\, z\, [s \neq z \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x',z,t')] \rightarrow P(x,t) < P(x',t')]$

Proof – On the basis of the relative uncertainty, quality, and status, definition 6.9 can be used to determine the relative perceived quality within a technological system. Next, on the basis of this relative perceived quality we use postulate 6.14 to get the relative ability to mobilize resources with that technological system, and in combination with the ability to mobilize resources in the alternative technological domains, we can use definition 6.10 to aggregate the ability to mobilize resources to the organizational level, while postulate 6.15 can subsequently be employed to determine the relative performance.

Initial condition Theorem 6.11

$UC(s,t) < UC(s,t') \wedge Q(x,s,t) \leq Q(x',s,t') \wedge S(x,s,t) \leq S(x',s,t') \wedge Q(x,s,t) < S(x,s,t) \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x',z,t')$

Formal proof

D6.9: $UC(s,t) < UC(s,t') \wedge Q(x,s,t) \leq Q(x',s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) < S(x,s,t) \rightarrow PQ(x,s,t) < PQ(x',s,t')$[34]

P6.14: $PQ(x,s,t) < PQ(x,s,t') \rightarrow MR(x,s,t) < MR(x',s,t')$

D6.10: $MR(x,s,t) < MR(x',s,t') \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x',z,t') \rightarrow MR(x,t) < MR(x',t')$

P6.15: $MR(x,t) < MR(x',t') \rightarrow P(x,t) < P(x',t')$

Q.E.D.

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[34] The reason that the relative perceived quality logically follows is that, because the level of uncertainty is smaller than 1, $Q(x,s,t) - Q(x',s,t') + UC(s,t) * (S(x,s,t) - Q(x,s,t)) - UC(s,t') * (S(x',s,t') - Q(x',s,t'))$ is always smaller than 0

Theorem 6.12

$\mathfrak{P}\ x,x',s,t,t'\ [UC(s,t) > UC(s,t') \wedge Q(x',s,t') \leq Q(x',s,t) \wedge S(x,s,t) \leq S(x,s,t') \wedge$

$Q(x,s,t) > S(x,s,t) \wedge \forall\ z\ [s \neq z \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x',z,t')] \ \rightarrow\ P(x,t) < P(x',t')]$

Proof – On the basis of the relative uncertainty, quality, and status, definition 6.9 can be used to determine the relative perceived quality within a technological system. Next, on the basis of this relative perceived quality we use postulate 6.14 to get the relative ability to mobilize resources with that technological system, and in combination with the ability to mobilize resources in the alternative technological domains, we can use definition 6.10 to aggregate the ability to mobilize resources to the organizational level, while postulate 6.15 can subsequently be employed to determine the relative performance.

Initial condition Theorem 6.12

$UC(s,t) > UC(s,t') \wedge Q(x,s,t) \leq Q(x',s,t') \wedge S(x,s,t) \leq S(x',s,t') \wedge Q(x,s,t) > S(x,s,t) \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x',z,t')$

Formal proof

D6.9: $UC(s,t) > UC(s,t') \wedge Q(x,s,t) \leq Q(x',s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) > S(x,s,t) \rightarrow PQ(x,s,t) < PQ(x',s,t')$[35]

P6.14: $PQ(x,s,t) < PQ(x,s,t') \rightarrow\ MR(x,s,t) < MR(x',s,t')$

D6.10: $MR(x,s,t) < MR(x',s,t') \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x',z,t') \rightarrow\ MR(x,t) < MR(x',t')$

P6.15: $MR(x,t) < MR(x',t') \rightarrow\ P(x,t) < P(x',t')$

Q.E.D.

Theorem 6.13

$\mathfrak{P}\ x,s,t,t'\ [G(s,t) \wedge t' > t \wedge Q(x,s,t) \leq Q(x,s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t)$

$> S(x,s,t)\ \wedge \forall\ z\ [s \neq z \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x',z,t')] \rightarrow\ P(x,t) < P(x,t')]$

Proof – On the basis postulate 6.3, we can determine the relative uncertainty at the different points in time in the technological system. Then, on the basis of the relative uncertainty, quality, and status, definition 6.9 can be used to determine the relative perceived quality within a technological system. Next, on the basis of this relative perceived quality we use postulate 6.14 to get the relative ability to mobilize resources

[35] The reason that the relative perceived quality logically follows is that, because the level of uncertainty is smaller than 1, $Q(x,s,t) - Q(x',s,t') + UC(s,t) * (S(x,s,t) - Q(x,s,t)) - UC(s,t') * (S(x',s,t') - Q(x',s,t'))$ is always smaller than 0

with that technological system, and in combination with the ability to mobilize resources in the alternative technological domains, we can use definition 6.10 to aggregate the ability to mobilize resources to the organizational level, while postulate 6.15 can subsequently be employed to determine the relative performance.

Initial condition Theorem 6.13

$G(s,t) \wedge t' > t \wedge Q(x,s,t) \leq Q(x,s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) > S(x,s,t) \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x',z,t')$

Formal proof

P6.3: $G(s,t) \wedge t' > t \rightarrow UC(s,t) < UC(s,t')$

D6.9: $UC(s,t) < UC(s,t') \wedge Q(x,s,t) \leq Q(x',s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) > S(x,s,t) \rightarrow PQ(x,s,t) < PQ(x',s,t')$[36]

P6.14: $PQ(x,s,t) < PQ(x,s,t') \rightarrow MR(x,s,t) < MR(x',s,t')$

D6.10: $MR(x,s,t) < MR(x',s,t') \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x',z,t') \rightarrow MR(x,t) < MR(x',t')$

P6.15: $MR(x,t) < MR(x',t') \rightarrow P(x,t) < P(x',t')$

Q.E.D.

Theorem 6.14

$\mathfrak{P}\ x,s,t,t'\ [\neg G(s,t) \wedge G(s,t') \wedge Q(x,s,t) \leq Q(x,s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) > S(x,s,t) \wedge \forall z\ [s \neq z \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x,z,t')] \rightarrow P(x,t) < P(x,t')]$

Proof – On the basis postulate 6.2, we can determine the relative uncertainty at the points in time in the technological system. Then, on the basis of the relative uncertainty, quality, and status, definition 6.9 can be used to determine the relative perceived quality within a technological system. Next, on the basis of this relative perceived quality we use postulate 6.14 to get the relative ability to mobilize resources with that technological system, and in combination with the ability to mobilize resources in the alternative technological domains, we can use definition 6.10 to aggregate the ability to mobilize resources to the organizational level, while postulate 6.15 can subsequently be employed to determine the relative performance.

[36] The reason that the relative perceived quality logically follows is that, because the level of uncertainty is smaller than 1, $Q(x,s,t) - Q(x',s,t') + UC(s,t) * (S(x,s,t) - Q(x,s,t)) - UC(s,t') * (S(x',s,t') - Q(x',s,t'))$ is always smaller than 0

Initial condition Theorem 6.14

$\neg G(s,t) \wedge G(s,t') \wedge Q(x,s,t) \leq Q(x,s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) > S(x,s,t) \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x,z,t')$

Formal proof

P6.2: $\neg G(s,t) \wedge G(s,t') \rightarrow UC(s,t) < UC(s,t')$

D6.9: $UC(s,t) < UC(s,t') \wedge Q(x,s,t) \leq Q(x',s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) > S(x,s,t) \rightarrow PQ(x,s,t) < PQ(x',s,t')$[37]

P6.14: $PQ(x,s,t) < PQ(x,s,t') \rightarrow MR(x,s,t) < MR(x',s,t')$

D6.10: $MR(x,s,t) < MR(x',s,t') \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x',z,t') \rightarrow MR(x,t) < MR(x',t')$

P6.15: $MR(x,t) < MR(x',t') \rightarrow P(x,t) < P(x',t')$

Q.E.D.

Theorem 6.15

$\mathfrak{P}\ x,s,t,t'\ [G(s,t) \wedge t > t' \wedge Q(x,s,t) \leq Q(x,s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) < S(x,s,t) \wedge \forall z\ [s \neq z \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x,z,t')] \rightarrow P(x,t) < P(x,t')]$

Proof – On the basis postulate 6.3, we can determine the relative uncertainty at the points in time in the technological system. Then, on the basis of the relative uncertainty, quality, and status, definition 6.9 can be used to determine the relative perceived quality within a technological system. Next, on the basis of this relative perceived quality we use postulate 6.14 to get the relative ability to mobilize resources with that technological system, and in combination with the ability to mobilize resources in the alternative technological domains, we can use definition 6.10 to aggregate the ability to mobilize resources to the organizational level, while postulate 6.15 can subsequently be employed to determine the relative performance.

Initial condition Theorem 6.15

$G(s,t) \wedge t > t' \wedge Q(x,s,t) \leq Q(x,s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) < S(x,s,t) \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x,z,t')$

Formal proof

P6.3: $G(s,t) \wedge t > t' \rightarrow UC(s,t) > UC(s,t')$

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[37] The reason that the relative perceived quality logically follows is that, because the level of uncertainty is smaller than 1, $Q(x,s,t) - Q(x',s,t') + UC(s,t) * (S(x,s,t) - Q(x,s,t)) - UC(s,t') * (S(x',s,t') - Q(x',s,t'))$ is always smaller than 0

D6.9: $UC(s,t) > UC(s,t') \wedge Q(x,s,t) \leq Q(x',s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) > S(x,s,t) \rightarrow PQ(x,s,t) < PQ(x',s,t')$[38]

P6.14: $PQ(x,s,t) < PQ(x,s,t') \rightarrow MR(x,s,t) < MR(x',s,t')$

D6.10: $MR(x,s,t) < MR(x',s,t') \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x',z,t') \rightarrow MR(x,t) < MR(x',t')$

P6.15: $MR(x,t) < MR(x',t') \rightarrow P(x,t) < P(x',t')$

Q.E.D.

Theorem 6.16

$\mathfrak{P}\ x,s,t,t'\ [\neg G(s,t') \wedge G(s,t) \wedge Q(x,s,t) \leq Q(x,s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) < S(x,s,t) \wedge \forall z\ [s \neq z \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x,z,t')] \rightarrow P(x,t) < P(x,t')]$

Proof – On the basis postulate 6.2, we can determine the relative uncertainty at the points in time in the technological system. Then, on the basis of the relative uncertainty, quality, and status, definition 6.9 can be used to determine the relative perceived quality within a technological system. Next, on the basis of this relative perceived quality we use postulate 6.14 to get the relative ability to mobilize resources with that technological system, and in combination with the ability to mobilize resources in the alternative technological domains, we can use definition 6.10 to aggregate the ability to mobilize resources to the organizational level, while postulate 6.15 can subsequently be employed to determine the relative performance.

Initial condition Theorem 6.16

$\neg G(s,t) \wedge G(s,t') \wedge Q(x,s,t) \leq Q(x,s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) > S(x,s,t) \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x,z,t')$

Formal proof

P6.2: $\neg G(s,t) \wedge G(s,t') \rightarrow UC(s,t) > UC(s,t')$

D6.9: $UC(s,t) > UC(s,t') \wedge Q(x,s,t) \leq Q(x',s,t') \wedge S(x,s,t) \leq S(x,s,t') \wedge Q(x,s,t) > S(x,s,t) \rightarrow PQ(x,s,t) < PQ(x',s,t')$[39]

P6.14: $PQ(x,s,t) < PQ(x,s,t') \rightarrow MR(x,s,t) < MR(x',s,t')$

D6.10: $MR(x,s,t) < MR(x',s,t') \wedge \sum_z MR(x,z,t) \leq \sum_z MR(x',z,t') \rightarrow MR(x,t) < MR(x',t')$

[38] The reason that the relative perceived quality logically follows is that, because the level of uncertainty is smaller than 1, $Q(x,s,t) – Q(x',s,t') + UC(s,t) * (S(x,s,t) - Q(x,s,t)) – UC(s,t') * (S(x',s,t') - Q(x',s,t'))$ is always smaller than 0

[39] The reason that the relative perceived quality logically follows is that, because the level of uncertainty is smaller than 1, $Q(x,s,t) – Q(x',s,t') + UC(s,t) * (S(x,s,t) - Q(x,s,t)) – UC(s,t') * (S(x',s,t') - Q(x',s,t'))$ is always smaller than 0

P6.15: $MR(x,t) < MR(x',t') \rightarrow P(x,t) < P(x',t')$

Q.E.D.

Theorem 6.17

$\mathfrak{P}\ x,x',d,t,t'\ [D(x,d,t) > D(x',d,t') \wedge M(x,d,t) \geq M(x',d,t') \wedge M(x',d,t') > 0 \rightarrow P(x,t) > P(x',t')]$

Proof – On the basis of the relative diversity and the relative diversity multipliers, postulate 6.17 gives the relative opportunities, and postulate 6.21 can subsequently be used to determine the relative performance of focal and alter

Initial condition Theorem 6.17

$D(x,d,t) > D(x',d,t') \wedge M(x,d,t) \geq M(x',d,t') \wedge M(x',d,t') > 0$

Formal proof

P6.17: $D(x,d,t) > D(x',d,t') \wedge M(x,d,t) \geq M(x',d,t') \wedge M(x',d,t') > 0 \rightarrow Opp(x,t) > Opp(x',t')$

P6.21: $Opp(x,t) > Opp(x',t') \rightarrow P(x,t) > P(x',t')$

Q.E.D.

Theorem 6.18

$\mathfrak{P}\ x,x',d,t,t'\ [D(x,d,t) > D(x',d,t') \wedge M(x,d,t) \leq M(x',d,t') \wedge M(x',d,t') < 0 \rightarrow P(x,t) < P(x',t')]$

Proof – On the basis of the relative diversity and the relative diversity multipliers, postulate 6.18 gives the relative costs, and postulate 6.22 can subsequently be used to determine the relative performance of focal and alter

Initial condition Theorem 6.18

$D(x,d,t) > D(x',d,t') \wedge M(x,d,t) \leq M(x',d,t') \wedge M(x',d,t') < 0$

Formal proof

P6.18: $D(x,d,t) > D(x',d,t') \wedge M(x,d,t) \leq M(x',d,t') \wedge M(x',d,t') < 0 \rightarrow Costs(x,t) > Costs(x',t')$

P6.22: $Costs(x,t) > Costs(x',t') \rightarrow P(x,t) > P(x',t')$

Q.E.D.

Theorem 6.19

$\mathfrak{P}\, x,x',d,t,t'\ [D(x,d,t) \geq D(x',d,t') \wedge M(x,d,t) > M(x',d,t') \wedge M(x',d,t') > 0 \rightarrow P(x,t) > P(x',t')]$

Proof – On the basis of the relative diversity and the relative diversity multipliers, postulate 6.19 gives the relative opportunities, and postulate 6.21 can subsequently be used to determine the relative performance of focal and alter

Initial condition Theorem 6.19

$D(x,d,t) \geq D(x',d,t') \wedge M(x,d,t) > M(x',d,t') \wedge M(x',d,t') > 0$

Formal proof

P6.19: $D(x,d,t) \geq D(x',d,t') \wedge M(x,d,t) > M(x',d,t') \wedge M(x',d,t') > 0 \rightarrow Opp(x,t) > Opp(x',t')$

P6.21: $Opp(x,t) > Opp(x',t') \rightarrow P(x,t) > P(x',t')$

Q.E.D.

Theorem 6.20

$\mathfrak{P} x,x',r,t,t'\ [D(x,d,t) \geq D(x',d,t') \wedge M(x,d,t) < M(x',d,t') \wedge M(x',d,t') < 0 \rightarrow P(x,t) < P(x',t')]$

Proof – On the basis of the relative diversity and the relative diversity multipliers, postulate 6.20 gives the relative costs, and postulate 6.22 can subsequently be used to determine the relative performance of focal and alter

Initial condition Theorem 6.20

$D(x,d,t) \geq D(x',d,t') \wedge M(x,d,t) < M(x',d,t') \wedge M(x',d,t') < 0$

Formal proof

P6.20: $D(x,d,t) \geq D(x',d,t') \wedge M(x,d,t) < M(x',d,t') \wedge M(x',d,t') < 0 \rightarrow Costs(x,t) > Costs(x',t')$

P6.22: $Costs(x,t) > Costs(x',t') \rightarrow P(x,t) > P(x',t')$

Q.E.D.

Theorem 6.21

$\mathfrak{P}\, x,s,t,t'\ [\tau_{xst} = \tau_{xst'} \wedge TO(s,t) > TO(s,t') \wedge \forall\, w\ [s \neq w\ \wedge \sum_w \tau_{xwt} \cdot TO(w,t) \geq \sum_w \tau_{xwt'} \cdot TO(w,t')] \rightarrow P(x,t) > P(x,t')]$

Proof – On the basis of our initial assumptions, we can use definition 6.14 to get the relative technological opportunities at the organizational level of analysis. Postulate 6.23 can then be used to determine the relative opportunities, while postulate 6.21 gives the relative performance between focal and alter.

Initial condition Theorem 6.21

$\tau_{xst} = \tau_{xst'} \wedge TO(s,t) > TO(s,t') \wedge \sum_w \tau_{xwt} \cdot TO(w,t) \geq \sum_w \tau_{xwt'} \cdot TO(w,t')$

Formal proof

D6.14: $\tau_{xst} = \tau_{xst'} \wedge TO(s,t) > TO(s,t') \wedge \sum_w \tau_{xwt} \cdot TO(w,t) \geq \sum_w \tau_{xwt'} \cdot TO(w,t') \rightarrow TO(x,t) > TO(x',t')$

P6.23: $TO(x,t) > TO(x',t') \rightarrow Opp(x,t) > Opp(x',t')$

P6.21: $Opp(x,t) > Opp(x',t') \rightarrow P(x,t) > P(x',t')$

Q.E.D.

Theorem 6.22

$\mathfrak{P}\ x,x',s,t,t'\ [\tau_{xst} > \tau_{x'st'} \wedge \forall\ w\ [TO(s,t) > TO(w,t')] \wedge \forall\ z\ [z \neq w \wedge \sum_z \tau_{xzt} \cdot TO(z,t) \geq \sum_z \tau_{xzt'} \cdot TO(z,t')] \rightarrow P(x,t) > P(x',t')]$

Proof – On the basis of our initial assumptions, we can use definition 6.14 to get the relative technological opportunities at the organizational level of analysis. Postulate 6.23 can then be used to determine the relative opportunities, while postulate 6.21 gives the relative performance between focal and alter.

Initial condition Theorem 6.22

$\tau_{xst} > \tau_{x'st'} \wedge TO(s,t) > TO(w,t') \wedge \sum_z \tau_{xzt} \cdot TO(z,t) \geq \sum_z \tau_{xzt'} \cdot TO(z,t')$

Formal proof

D6.14: $\tau_{xst} > \tau_{x'st'} \wedge TO(s,t) > TO(w,t') \wedge \sum_z \tau_{xzt} \cdot TO(z,t) \geq \sum_z \tau_{xzt'} \cdot TO(z,t')$

P6.23: $TO(x,t) > TO(x',t') \rightarrow Opp(x,t) > Opp(x',t')$

P6.21: $Opp(x,t) > Opp(x',t') \rightarrow P(x,t) > P(x',t')$

Q.E.D.

Appendix K

Regression estimates

Table K.1 Restricted negative binomial panel regression estimates

	1. RE NB R	2. CFE NB R	3. UFE NB R
Biotechnology crowding (thousands)	-5.931***	-7.024***	-9.096***
	[0.801]	[0.877]	[0.852]
Biotechnology non-crowding (millions)	-34.151***	-19.342***	-16.379***
	[6.746]	[6.550]	[5.143]
Biotechnology status	-4.424	-18.165***	-19.180**
	[6.572]	[7.002]	[7.574]
Biotechnology quality	67.959***	73.983***	72.934***
	[6.491]	[6.763]	[7.440]
Biotechnology opportunities	2.786***	2.577***	1.595**
	[0.652]	[0.721]	[0.749]
Global antecedent diversity	0.609***	0.686***	0.727***
	[0.083]	[0.091]	[0.093]
Global focal diversity	-0.121	-0.210**	-0.507***
	[0.089]	[0.100]	[0.108]
Global descendant diversity	-0.173***	-0.098	0.250***
	[0.058]	[0.064]	[0.070]
Bio-antecedent diversity	0.01	0.014	-0.131**
	[0.053]	[0.056]	[0.053]
Bio-focal diversity	0.350***	0.203***	0.242***
	[0.051]	[0.053]	[0.053]
Bio-descendant diversity	-0.125***	-0.185***	-0.297***
	[0.046]	[0.048]	[0.051]
Previous entries	0.003***	0.003***	0.008***
	[0.001]	[0.001]	[0.001]
Biotechnology focus	0.870***	0.178	-0.241
	[0.165]	[0.204]	[0.266]
Biotechnology density (thousands)	0.772***	0.614***	0.814***
	[0.162]	[0.173]	[0.184]
Global density (millions)	-2.895	-3.109	-9.270*
	[4.005]	[4.374]	[5.071]
Age (thousands)	3.033***		
	[0.522]		
LN(Employees (thousands))	0.065***	0.043*	0.095***
	[0.022]	[0.022]	[0.023]
LN(R&D expenditures (trillion $))	0.183	0.103	0.225
	[0.178]	[0.065]	[0.209]
LN(Revenues (trillion $))	-0.168***	-0.079**	-0.227***
	[0.040]	[0.039]	[0.042]
LN(Assets (billion $))	0.054*	0.086***	0.072**
	[0.030]	[0.031]	[0.035]
Constant	-0.68		
	[0.798]		
Alpha			0.168***
			[0.007]
r, of Beta(r,s)	3.292***		
	[0.291]		
s, of Beta(r,s)	4.692***		
	[0.509]		
Observations	4,896	4,838	4,896
Number of organizations	441	417	441
Degrees of freedom	43	42	483
Log likelihood	-11,826	-9,692	-10,968

Legend: * significant at 10; ** significant at 5; *** significant at 1; standard errors in brackets.

Table K.2 Unrestricted negative binomial panel regression estimates

	4. RE NB U	5. CFE NB U	6. UFE NB U
Biotechnology crowding (thousands)	-6.020***	-9.878***	-9.25***
	[0.516]	[0.566]	[0.52]
Biotechnology non-crowding (millions)	-29.503***	-30.475***	-11.275***
	[3.305]	[3.546]	[2.548]
Biotechnology status	-1.439	-10.469**	-13.958**
	[4.743]	[4.946]	[5.895]
Biotechnology quality	84.723***	90.424***	99.192***
	[4.570]	[4.723]	[5.852]
Biotechnology opportunities	3.191***	2.862***	4.968***
	[0.334]	[0.336]	[0.388]
Global antecedent diversity	0.261***	0.187***	0.293***
	[0.044]	[0.046]	[0.05]
Global focal diversity	0.121**	0.044	0.178***
	[0.052]	[0.054]	[0.062]
Global descendant diversity	-0.139***	-0.244***	-0.078**
	[0.032]	[0.032]	[0.038]
Bio-antecedent diversity	-0.03	-0.219***	-0.132***
	[0.031]	[0.030]	[0.032]
Bio-focal diversity	0.322***	0.263***	0.226***
	[0.029]	[0.029]	[0.031]
Bio-descendant diversity	-0.071***	-0.240***	-0.254***
	[0.027]	[0.026]	[0.030]
Previous entries	0.007***	0.008***	0.016***
	[0.001]	[0.001]	[0.001]
Biotechnology focus	0.197**	-0.796***	0.312***
	[0.086]	[0.088]	[0.121]
Biotechnology density (thousands)	-0.131	-0.886***	-1.331***
	[0.112]	[0.114]	[0.129]
Global density (millions)	3.517	8.414***	2.202
	[2.344]	[2.515]	[3.059]
Constant	-2.429***		
	[0.112]		
Alpha			0.239***
			[0.007]
r, of Beta(r,s)	3.228***		
	[0.175]		
s, of Beta(r,s)	3.421***		
	[0.215]		
Observations	14,186	14,133	14,186
Number of organizations	921	907	921
Degrees of freedom	38	38	959
Log likelihood	-26,987	-22,859	-25,426

Legend: * significant at 10; ** significant at 5; *** significant at 1; standard errors in brackets.

References

A

Abbernathy, W. J., & Utterback, J. M. 1978. Patterns of Industrial Innovation. ***Technology review***, 80: 41-47.

Ahuja, G., & Katila, R. 2004. Where Do Resources Come From? The Role of Idiosyncratic Situations. ***Strategic Management Journal***, 25: 887-907.

Albert, M. B., Avery, D., Narin, F., & McAllister, P. 1991. Direct Validation of Citation Counts as Indicators of Industrially Important Patents. ***Research Policy***, 20: 251-259.

Aldrich, H. E., & Fiol, C. M. 1994. Fools Rush in - the Institutional Context of Industry Creation. ***Academy of Management Review***, 19: 645-670.

Allison, P. D., & Waterman, R. P. 2002. Fixed-Effects Negative Binomial Regression Models. ***Sociological Methodology***, 32: 247-265.

Andersen, B. 1999. The Hunt for S-Shaped Growth Paths in Technological Innovation: A Patent Study. ***Journal of Evolutionary Economics***, 9: 487-526.

Anderson, P., & Tushman, M. L. 1990. Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. ***Administrative Science Quarterly***, 35: 604-633.

Andrianantoandro, E., Basu, S., Karig, D. K., & Weiss, R. 2006. Synthetic Biology: New Engineering Rules for an Emerging Discipline. ***Molecular Systems Biology***-.

B

Baldwin, C. Y., & Clark, K. B. 2000. ***Design Rules: The Power of Modularity***. Cambridge, Massachusetts: The MIT Press.

Barfield, C., & Calfee, J. E. 2007. ***Biotechnology and the Patent System: Balacing Innovation and Property Rights***. Washinton, D.C.: The AIE Press.

Barley, S. R. 1990. The Alignment of Technology and Structure through Roles and Networks. ***Administrative Science Quarterly***, 35: 61-103.

Barnett, W. P. 1990. The Organizational Ecology of a Technological System. ***Administrative Science Quarterly***, 35: 61-103.

Barnett, W. P. 1991. Strategic Deterrence among Multipoint Competitors. In L. R. Jauch, & J. L. Wall (Eds.), ***Academy of Management***. Miami, FL: Best paper proceedings: 7-10.

Barnett, W. P. 1997. The Dynamics of Competitive Intensity. ***Administrative Science Quarterly***, 42: 128-160.

Basalla, G. 1988. ***The Evolution of Technology***. Cambridge: Cambridge University Press.

Bass, F. M. 1969. New Product Growth for Model Consumer Durables. ***Management Science***, 15: 215-227.

Bass, F. M. 2004. Comments on "a New Product Growth for Model Consumer Durables". ***Management Science***, 50: 1833-1840.

Bauer, M. W. 2005. Public Perceptions and Mass Media in the Biotechnology Controversy. ***International Journal of Public Opinion Research***, 17: 5-22.

Baum, J. A. C. 1996. Organizational Ecology. In S. R. Clegg, C. Hardy, & Walter R. Nord (Eds.), ***Handbook of Organization Studies***: 77-114. London: Sage.

Baum, J. A. C. 1999. Whole-Part Coevolutionary Competition in Organizations. In J. A. C. Baum, & B. McKelvey (Eds.), ***Variations in Organization Science: In Honor or Donald T. Campbell***: 113-136. London: Sage.

Baum, J. A. C., & Haveman, H. A. 1997. Love Thy Neighbor? Differentiation and Agglomeration in the Manhattan Hotel Industry, 1898-1990. ***Administrative Science Quarterly***, 42: 304-338.

Baum, J. A. C., Korn, H. J., & Kotha, S. 1995. Dominant Designs and Population-Dynamics in Telecommunications Services - Founding and Failure of Facsimile Transmission Service Organizations, 1965-1992. ***Social Science Research***, 24: 97-135.

Baum, J. A. C., & Mezias, S. J. 1992. Localized Competition and Organizational Failure in the Manhattan Hotel Industry, 1898-1990. ***Administrative Science Quarterly***, 37: 580-604.

Baum, J. A. C., & Powell, W. W. 1995. Cultivating an Institutional Ecology of Organizations: Comments on Hannan, Carroll, Dundon, and Torres. ***American Sociological Review***, 60: 529-538.

Baum, J. A. C., & Shipilov, A. V. 2006. Ecological Approaches to Organizations. In S. R. Clegg, C. Hardy, & W. Nord (Eds.), ***Handbook of Organization Studies***: SAGE Publications.

Baum, J. A. C., & Singh, J. V. 1994a. Organization-Environment Coevolution. In J. A. C. Baum, & J. V. Singh (Eds.), ***Evolutionary Dynamics of Organizations***: 379-402. Oxford: Oxford University Press.

Baum, J. A. C., & Singh, J. V. 1994b. Organizational Niches and the Dynamics of Organizational Founding. ***Organization Science***, 5: 483-501.

Baum, J. A. C., & Singh, J. V. 1994c. Organizational Niches and the Dynamics of Organizational Mortality. ***American Journal of Sociology***, 100: 346-380.

Benner, M. J., & Tushman, M. L. 2002. Process Management and Technological Innovation: A Longitudinal Study of the Photography and Paint Industries. ***Administrative Science Quarterly***, 47: 676-706.

Benner, S. A., & Sismour, A. M. 2005. Synthetic Biology. ***Nature Reviews Genetics***, 6: 533-543.

Beuzekom, B. v., & Arundel, A. 2006. Oecd Biotechnology Statistics 2006. Paris, France: Organisation for Economic Co-operation and Development.

BIO. 2006. Guide to Biotechnology 2005-2006. Washington, DC: Biotechnology Industry Organization (Bio.org).

BIO. 2008. Guide to Biotechnology. Washington, DC: Biotechnology Industry Organization (Bio.org).

Bioworld. 2008. Bioworld State of the Industry Report. Available online at: www.bioworld.org.

Bogaert, S., Boone, C., & Carroll, G. R. 2007. Fuzzy Origins: Form Emergence among Competing Professional Schemata of Dutch Accounting, 1884-1939: Research paper. University of Antwerpen.

Boone, C., Wezel, F. C., & van Witteloostuijn, A. 2004. An Ecological Theory of Population-Level Diversity Dependence, ***Working paper***. University of Antwerp, Belgium.

Boone, C., Wezel, F. C., & van Witteloostuijn, A. 2007. En Ecological Theory of Population-Level Organizational Diversity: Research paper. University of Antwerpen.

Borgatti, S. P., Everett, M. G., & Freeman, L. C. 2002. Ucinet for Windows: Software for Social Network Analysis. Harvard: Analytic Technologies.

Botstein, D. 2004. An Introductory Science Curriculum for 21st Century Biologists. ***Symposium on Systems Biology at MIT***Available online at MIT World.

Bourzac, K. 2009. Speed-Reading DNA Inches Closer, ***Technology Review***, Vol. February 2009.

Bruggeman, J., & Vermeulen, I. 2002. A Logical Toolkit for Theory (Re)Construction. ***Sociological methodology***, 32: 183-217.

C

Cameron, A. C., & Trivedi, P. K. 1986. Econometric Models Based on Count Data: Comparisons and Applications of Some Estimators and Tests. ***Journal of Applied Econometrics***, 1: 29-53.

Cameron, A. C., & Trivedi, P. K. 1998. ***Regression Analysis of Count Data***. Cambridge, UK: Cambridge University Press.

Canton, B., Labno, A., & Endy, D. 2008. Refinement and Standardization of Synthetic Biological Parts and Devices. ***Nature Biotechnology***, 26: 787-793.

Carroll, G. R. 1984. Organizational Ecology. ***Annual Review of Sociology***, 10: 71-93.

Carroll, G. R., & Hannan, M. T. 1989a. Density Dependence in the Evolution of Populations of Newspaper Organizations. ***American Sociological Review***, 54: 524-541.

Carroll, G. R., & Hannan, M. T. 1989b. On Using Institutional Theory in Studying Organizational Populations - Reply. ***American Sociological Review***, 54: 545-548.

Carroll, G. R., & Hannan, M. T. 2000. ***The Demography of Corporations and Industries***. Princeton: Princeton University Press.

CDC. 2009. Costs of Cronic Disease. ***Centers for Disease control and prevention***.

Clark, K. 1985. The Interaction of Design Hierarchies and Market Concepts in Technological Evolution. ***Research Policy***, 14: 235-251.

Cohen, W. M., & Levinthal, D. A. 1990. Absorptive-Capacity - a New Perspective on Learning and Innovation. ***Administrative Science Quarterly***, 35: 128-152.

Cyert, R. M., & March, J. G. 1963. ***A Behavioral Theory of the Firm***. Upper Saddle River: NJ: Prentice Hall.

D

Delacroix, J., & Carroll, G. R. 1983. Organizational Foundings - an Ecological Study of the Newspaper Industries of Argentina and Ireland. ***Administrative Science Quarterly***, 28: 274-291.

Delacroix, J., & Rao, H. 1994. Externalities and Ecological Theory: Unbundling Density Dependence. In J. A. C. Baum, & J. V. Singh (Eds.), ***Evolutionary Dynamics of Organizations***: 225-268. New York: Oxford University Press.

Dimaggio, P. J., & Powell, W. W. 1983. The Iron Cage Revisited - Institutional Isomorphism and Collective Rationality in Organizational Fields. ***American Sociological Review***, 48: 147-160.

Dobrev, S. D., Kim, T.-Y., & Carroll, G. R. 2002a. The Evolution of Organizational Niches: Us Automobile Manufacturers, 1885-1981. ***Administrative Science Quarterly***, 47: 233-264.

Dobrev, S. D., Kim, T.-Y., & Hannan, M. T. 2001a. Dynamics of Niche Width and Resource Partitioning. ***American Journal of Sociology***, 106: 1299-1337.

Dobrev, S. D., Kim, T. Y., & Carroll, G. R. 2002b. The Evolution of Organizational Niches: Us Automobile Manufacturers, 1885-1981. ***Administrative Science Quarterly***, 47: 233-264.

Dobrev, S. D., Kim, T. Y., & Carroll, G. R. 2003. Shifting Gears, Shifting Niches: Organizational Inertia and Change in the Evolution of the Us Automobile Industry, 1885-1981. ***Organization Science***, 14: 264-282.

Dobrev, S. D., Kim, T. Y., & Hannan, M. T. 2001b. Dynamics of Niche Width and Resource Partitioning. ***American Journal of Sociology***, 106: 1299-1337.

Dosi, G. 1982. Technological Paradigms and Technological Trajectories. ***Research Policy***, 11: 147-162.

Dosi, G. 1984. ***Technical Change and Industrial Transformation: The Theory and an Application to the Semiconductor Industry***. London: The MacMillian Press.

Dosi, G. 1988. Sources, Procedures, and Microeconomic Effects of Innovation. ***Journal of Economic Literature***, 26: 1120-1171.

Doz, Y. L., & Hamel, G. 1998. ***Alliance Advantage: The Art of Creating Value through Partnering***. Boston, Massachusetts: Harvard University Press.

Durkheim, E. 1933. ***The Division of Labor in Society***. Ney York: Free Press.

Duysters, G. M. 1995. ***The Evolution of Complex Industrial Systems: The Dynamics of Major It Sectors***. Maastricht: Universitairy Pers Maastricht.

E

Elton, C. 1927. ***Animal Ecology***. London: Sidgwick and Jackson.

Endy, A. 2006. The Implications of Synthetic Biology. ***MIT Lecture***Available online at MIT World.

Endy, A., Thomas, J., & Brand, S. 2008. Drew Endy and Jim Thomas Debate Synthetic Biology. ***Long now foundation debate***Available online at fora.tv.

Endy, D. 2005. Foundations for Engineering Biology. ***Nature***, 438: 449-453.

ETC. 2007. Syndustry: The Emerging Synthetic Biology Industry. Ottawa, Canada: ETC Group.

F

Fedo, C. M., Whitehouse, M. J., & Kamber, B. S. 2006. Geological Constraints on Detecting the Earliest Life on Earth: A Perspective from the Early Archaean (Older Than 3.7 Gyr) of Southwest Greenland. ***Philosophical Transactions of the Royal Society B-Biological Sciences***, 361: 851-867.

Fisher, A. 1988. ***The Logic of Real Arguments***. Cambridge: Cambridge University Press.

Fleming, L. 2001. Recombinant Uncertainty in Technological Search. ***Management Science***, 47: 117-132.

Fleming, L., & Sorenson, O. 2001. Technology as a Complex Adaptive System: Evidence from Patent Data. ***Research Policy***, 30: 1019-1039.

Fleming, L., & Sorenson, O. 2004. Science as a Map in Technological Search. ***Strategic Management Journal***, 25: 909-928.

Foster, R. N. 1986. ***Innovation: The Attacker's Advantage***: Summit Books.

Freeman, J., & Hannan, M. T. 1983. Niche Width and the Dynamics of Organizational Populations. ***American Journal of Sociology***, 88: 1116-1145.

G

Gamut, L. T. F. 1991a. ***Logic, Language, and Meaning, Volume 1: Introduction to Logic***. Chicago: University of Chicago Press.

Gamut, L. T. F. 1991b. ***Logic, Language, and Meaning, Volume 2: Intensional Logic and Intentional Grammar***. Chicago: University of Chicago Press.

Gaskell, G. 2000. Agricultural Biotechnology and Public Attitudes in the European Union. ***AgBioForum***, 3: 87-96.

Gersick, C. J. G. 1991. Revolutionary Change Theories - a Multilevel Exploration of the Punctuated Equilibrium Paradigm. ***Academy of Management Review***, 16: 10-36.

Gibson, D. G., Benders, G. A., Andrews-Pfannkoch, C., Denisova, E. A., Baden-Tillson, H., Zaveri, J., Stockwell, T. B., Brownley, A., Thomas, D. W., Algire, M. A., Merryman, C., Young, L., Noskov, V. N., Glass, J. I., Venter, J. C., Hutchison, C. A., & Smith, H. O. 2008. Complete Chemical Synthesis, Assembly, and Cloning of a Mycoplasma Genitalium Genome. ***Science***, 319: 1215-1220.

Gilsing, V., & Nooteboom, B. 2006. Exploration and Exploitation in Innovation Systems, the Case of Pharmaceutical Biotechnology. ***Research Policy***, 35: 1-23.

Goujon, P. 2001. ***From Biotechnology to Genomes: The Meaning of the Double Helix***. London: World Scientific.

Gould, S. J., & Eldregde, N. 1972. Punctuated Equilibria: An Alternative to Phyletic Gradualism. ***Models in Paleobiology***115-151.

Gray, M. L. 2005. Bioengineering at Mit: Building Bridges between the Sciences, Engineering and Health Care (Part Two). ***MIT Lecture*** Available online at MIT World.

Greene, W. H. 2001. Estimating Econometric Models with Fixed Effects: Manuscript, Department of Economics, Stern School of Business, New York University.

Greene, W. H. 2003. ***Econometric Analysis***: Prentice Hall.

Griliches, Z. 1957. Hybrid Corn - an Exploration in the Economics of Technological-Change. ***Econometrica***, 25: 501-522.

Griliches, Z. 1981. Market Value, R-and-D, and Patents. ***Economics Letters***, 7: 183-187.

Griliches, Z. 1990. Patent Statistics as Economic Indicators - a Survey. ***Journal of Economic Literature***, 28: 1661-1707.

Guimarães, P. 2008. The Fixed Effects Negative Binomial Model Revisited. ***Economics Letters***, 99: 63-66.

H

Hall, B. H., Jaffe, A., & Trajtenberg, M. 2001a. Market Value and Patent Citations: A First Look. ***NBER Working paper series***, 7741: 1-47.

Hall, B. H., Jaffe, A., & Trajtenberg, M. 2005. Market Value and Patent Citations. ***Rand Journal of Economics***, 36: 16-38.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. 2001b. The Nber Patent Citation Data File: Lessons, Insights and Methodological Tools. ***NBER Working paper series***, 8498: 1-46.

Hannan, M. T. 1998. Rethinking Age Dependence in Organizational Mortality: Logical Formalizations. ***American Journal of Sociology***, 104: 126-164.

Hannan, M. T., & Carroll, G. R. 1992. ***Dynamics of Organizational Populations: Density, Legitimation, and Competition***. New York: Oxford University Press.

Hannan, M. T., Carroll, G. R., & Polos, L. 2003a. The Organizational Niche. ***Sociological Theory***, 21: 309-340.

Hannan, M. T., Carroll, G. R., & Pólos, L. 2003b. The Organizational Niche. ***Sociological theory***, 21: 309-340.

Hannan, M. T., Dundon, E. A., Carroll, G. R., & Torres, J. C. 1995. Organizational Evolution in a Multinational Context - Entries of Automobile Manufacturers in Belgium, Britain, France, Germany, and Italy. ***American Sociological Review***, 60: 509-528.

Hannan, M. T., & Freeman, J. 1977. The Population Ecology of Organizations. ***American Journal of Sociology***, 82: 929-964.

Hannan, M. T., & Freeman, J. 1984. Structural Inertia and Organizational-Change. ***American Sociological Review***, 49: 149-164.

Hannan, M. T., & Freeman, J. 1987. The Ecology of Organizational Founding - American Labor Unions, 1836-1985. ***American Journal of Sociology***, 92: 910-943.

Hannan, M. T., & Freeman, J. 1989. ***Organizational Ecology***: Harvard University Press.

Hannan, M. T., Pólos, L., & Carroll, G. R. 2007. ***Logics of Organization Theory: Audiences, Codes, and Ecologies***. Princeton: Princeton University Press.

Hausman, J., Hall, B. H., & Griliches, Z. 1984. Econometric Models for Count Data with an Application to the Patents-R&D Relationship. ***Econometrica***, 52: 909-938.

Hausman, J. A. 1978. Specification Tests in Econometrics. ***Econometrica***, 46: 1251-1271.

Hawley, A. H. 1986. ***Human Ecolgy: A Theoretical Essay***. Chicago: he University of Chicago Press.

Heeler, R. M., & Hustad, T. P. 1980. Problems in Predicting New Product Growth for Consumer Durables. ***Management Science***, 26: 1007-1020.

Henderson, R. M., & Clark, K. B. 1990. Architectural Innovation - the Reconfiguration of Existing Product Technologies and the Failure of Established Firms. ***Administrative Science Quarterly***, 35: 9-30.

Hood, L. 2004. Keynote Presentation: Academic Perspectives. ***Symposium on Systems Biology at MIT***Available online at MIT World.

Horvitz, H. R. 2002. Mit Nobel Prize in Physiology or Medicine Lecture. ***MIT Lecture***Available online at MIT World.

Hsiao, C. 2003. ***Analysis of Panel Data*** (second ed.). Cambridge, Massachusetts: Cambridge University Press.

Hutchinson, G. E. 1959. Homage to Santa Rosalia or Why Are There So Many Kinds of Animals? ***The American Naturalist***, 93: 145-159.

J

Jaffe, A. B. 1986. Technological Opportunity and Spillovers of R&D: Evidence from Firm's Patents, Profits and Market Value. ***American Economic Review***, 76: 984-1001.

Jaffe, A. B., Trajtenberg, M., & Fogarty, M. S. 2000. Knowledge Spillovers and Patent Citations: Evidence from a Survey of Inventors. ***American Economic Review***, 90: 215-218.

Johnson, B. 1992. Institutional Learning. In B. Lundvall (Ed.), ***National Systems of Innovation***. London: Pinter.

Jones, D. 2005. Biotech: Investing Beyond the Hype. New York: Young Venture Capital Society: Available online at: www.yvcs.com.

de Jong, G., & van Witteloostuijn, A. 2008. Changing National Rules: Theory and Evidence for the Netherlands (1960-2004). ***Public Administration***, 86: 499-522.

K

Kass, L. R. 2003. Beyond Therapy: Biotechnology and the Pursuit of Happiness. Washington, D.C.: Government printing office.

Katz, M. L., & Shapiro, C. 1986. Technology Adoption in the Presence of Network Externalities. ***Journal of Political Economy***, 94: 822-841.

Kauffman, S. 1993. ***The Origins of Order: Self-Organization and Selection in Evolution***: Oxford University Press.

Klepper, S. 1997. Industry Life Cycles. ***Industrial and Corporate Change***, 6: 145-182.

Knight, F. H. 1921. ***Risk, Uncertainty, and Profit***. Boston, MA: Houghton Mifflin Co.

Korn, D., & Heinig, S. J. 2002. Public Versus Private Ownership of Scientific Discovery: Legal and Economic Analyses of the Implications of Human Gene Patents - Introduction: Patents, Genomics, and Academic Medicine. ***Academic Medicine***, 77: 1301-1308.

Kuhn, T. S. 1996. ***The Structure of Scientific Revolutions*** (third ed.). Chicago: The University of Chicago Press.

Kuilman, J., Vermeulen, I., & Li, J. 2007. The Consequents of Organizer Ecologies: A Logical Formalization: Research paper. Hong Kong University of Science and Technology.

Kuldell, N., & Shetty, R. 2009. Do-It-Yourself Biology. ***MIT Lecture***Available online at MIT World.

Kurzweil, R., & Joy, B. 2005. Recipe for Destruction, ***New York Times***. New York.

L

Lakatos, I. 1976. ***Proofs and Refutations: The Logic of Mathematical Discovery***. Cambridge: Cambridge University Press.

Lanjouw, J. O., & Schankeman, M. 2004. Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators. ***Economic Journal***, 114: 441-465.

Lanjouw, J. O., & Schankerman, M. 1999. The Quality of Ideas: Measuring Innovation with Multiple Indicators. ***NBER Working paper series***, 7345: 1-36.

Lauffenburger, D. A. 2005. Bioengineering Aqt Mit: Building Bridges between the Sciences, Engineering, and Health Care (Part One). ***MIT Lecture***Available online at MIT World.

Lawless, M. W., & Anderson, P. C. 1996. Generational Technological Change: Effects of Innovation and Local Rivalry on Performance. ***Academy of Management Journal***, 39: 1185-1217.

Lawrence, S. 2004. Patent Drop Reveals Pressures on Industry. ***Nature Biotechnology***, 22: 930-931.

Levin, R. C. 1988. Appropriability, R-and-D Spending, and Technological Performance. ***American Economic Review***, 78: 424-428.

Levinthal, D. A., & March, J. G. 1993. The Myopia of Learning. ***Strategic Management Journal***, 14: 95-112.

Lewin, A. Y., & Volberda, H. W. 1999. Prolegomena on Coevolution: A Framework for Research on Strategy and New Organizational Forms. ***Organization Science***, 10: 519-534.

Lite, J. 2009. Obama Ends Embryonic Stem Cell Research Ban. ***60-Second Science Blog***.

Lomi, A. 1995. The Population Ecology of Organizational Founding - Location Dependence and Unobserved Heterogeneity. ***Administrative Science Quarterly***, 40: 111-144.

M

MacArthur, R. H. 1965. Patterns of Species Diversity. ***Biological Review***, 40: 510-533.

MacArthur, R. H. 1972. ***Geographical Ecology***. New York: Harper & Row.

Mansfield, E. 1961. Technical Change and the Rate of Imitation. ***Econometrica***, 29: 741-766.

March, J. G., Schulz, M., & Shou, X. 2000. ***The Dynamics of Rules: Change in Written Organizational Rules***. Stanford: Stanford University Press.

March, J. S. 1991. Exploration and Exploitation in Organizational Learning. ***Organization Science***, 2: 71-87.

Marx, K. 1906. ***Capital***. Chicago: C.H. Kerr.

McKendrick, D. G., Jaffee, J., Carroll, G. R., & Khessina, O. M. 2003. In the Bud? Disk Array Producers as a (Possibly) Emergent Organizational Form. ***Administrative Science Quarterly***, 48: 60-93.

McPherson, M. 1983. An Ecology of Affiliation. ***American Sociological Review***, 48: 519-532.

Mead, C., & Conway, L. 1980. ***Introduction to Vlsi Systems***. Reading: Addison Wesley.

Merton, R. K. 1968a. The Matthew Effect in Science: The Reward and Communication Systems of Science Are Considered. ***Science***, 159: 56-63.

Merton, R. K. 1968b. ***Social Theory and Social Structure***. New York: Free Press.

Meyer, J. W., & Rowan, B. 1977. Institutionalized Organizations - Formal-Structure as Myth and Ceremony. ***American Journal of Sociology***, 83: 340-363.

Meyer, R. R. 2003. ***Genetics Encyclopedia: History of Biotechnology and Genetic Engineering***: The Gale Group, Inc.: Available online at answer.com.

Miller, H. I. 2007. Biotech's Defining Moments. ***Trends in Biotechnology***, 25: 56-59.

Moore, G. E. 1965. Cramming More Components onto Integrated Circuits. ***Electronics***, 38.

Mueller, D. C., & Tilton, J. E. 1969. Research and Development Costs as a Barrier to Entry. ***The Canadian Journal of Economics***570-579.

Nadel, S. F. 1957. ***The Theory of Social Structure***. London: Cohen and West.

N

Nelson, R. R. 2008. Factors Affecting the Power of Technological Paradigms. ***Industrial and Corporate Change***, 17: 485-497.

Nelson, R. R., & Winter, S. G. 1982. ***An Evolutionary Theory of Economic Change***. Cambridge, Massachusetts: The Belknap Press of Harvard University Press.

Nesta, L., & Saviotti, P. P. 2005. Coherence of the Knowledge Base and the Firm's Innovative Performance: Evidence from the Us Pharmaceutical Industry. ***Journal of Industrial Economics***, 53: 123-142.

Nightingale, P. 2008. Meta-Paradigm Change and the Theory of the Firm. ***Industrial and Corporate Change***, 17: 533-583.

Nightingale, P., & Martin, P. 2004. The Myth of the Biotech Revolution. ***Trends in Biotechnology***, 22: 564-569.

NIH. 2008. ***Stem Cell Basics***: National Institutes of Health. Available online at: http://stemcells.nih.gov/info/basics/.

Nooteboom, B. 2000. ***Learning and Innovation in Organizations and Economies***. Oxford: Oxford University Press.

Nooteboom, B., Vanhaverbeke, W., Duysters, G., Gilsing, V., & van den Oord, A. 2007. Optimal Cognitive Distance and Absorptive Capacity. ***Research Policy***, 36: 1016-1034.

O

Orlikowski, W. J. 1992. The Duality of Technology - Rethinking the Concept of Technology in Organizations. ***Organization Science***, 3: 398-427.

Orsenigo, L., Pammolli, F., & Riccaboni, M. 2001. Technological Change and Network Dynamics - Lessons from the Pharmaceutical Industry. ***Research Policy***, 30: 485-508.

P

Paine, J. A., Shipton, C. A., Chaggar, S., Howells, R. M., Kennedy, M. J., Vernon, G., Wright, S. Y., Hinchliffe, E., Adams, J. L., Silverstone, A. L., & Drake, R. 2005. Improving the Nutritional Value of Golden Rice through Increased Pro-Vitamin a Content. ***Nature Biotechnology***, 23: 482-487.

Pavitt, K. 1984. Sectoral Patterns of Innovation. ***Research Policy***, 13: 343-373.

Peli, G. 1997. The Niche Hiker's Guide to Population Ecology: A Logical Reconstruction of Organization Ecology's Niche Theory. ***Sociological Methodology 1997, Vol 27***, 27: 1-46.

Péli, G. 1997. The Niche Hiker's Guide to Population Ecology: A Logical Reconstruction of Organization Ecology's Niche Theory. ***Sociological Methodology 1997, Vol 27***, 27: 1-46.

Péli, G. 2007. Fit by Founding, Fit by Adaptation: Reconciling Conflicting Organization Theories with Logical Formalization: Research Paper. University of Groningen.

Péli, G., Bruggeman, J., Masuch, M., & Nuallain, B. O. 1994. A Logical Approach to Formalizing Organizational Ecology. ***American Sociological Review***, 59: 571-593.

Péli, G., & Masuch, M. 1997. The Logic of Propagation Strategies: Axiomatizing a Fragment of Organizational Ecology in First-Order Logic. ***Organization Science***, 8: 310-331.

Péli, G., & Nooteboom, B. 1999. Market Partitioning and the Geometry of the Resource Space. ***American Journal of Sociology***, 104: 1132-1153.

Pielou, E. 1969. ***An Introduction to Mathematical Ecology***. New York: Wiley.

Pisano, G. P. 2006. ***Science Business: The Promise, the Reality, and the Future of Biotech***. Boston, Massachusetts: Harvard Business School Press.

Pistorius, C. W. I., & Utterback, J. M. 1997. Multi-Mode Interaction among Technologies. ***Research Policy***, 26: 67-84.

Podolny, J. M. 1993. A Status-Based Model of Market Competition. ***American Journal of Sociology***, 98: 829-872.

Podolny, J. M. 1994. Market Uncertainty and the Social Character of Economic Exchange. ***Administrative Science Quarterly***, 39: 458-483.

Podolny, J. M., & Stuart, T. E. 1995. A Role-Based Ecology of Technological-Change. ***American Journal of Sociology***, 100: 1224-1260.

Podolny, J. M., Stuart, T. E., & Hannan, M. T. 1996. Networks, Knowledge, and Niches: Competition in the Worldwide Semiconductor Industry, 1984-1991. ***American Journal of Sociology***, 102: 659-689.

Pontikes, E. G. 2007. Knowledge Sharing or Competition? How Knowledge Space Crowding Affects Knowledge Progress and Market Survival: Research paper. Graduate School of Business, Stanford University.

Popper, K. 1963. ***Conjectures and Refutations***. London: Routledge.

Post. 2008. Synthetic Biology. ***Postnote***, 298.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. 1996. Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology. ***Administrative Science Quarterly***, 41: 116-145.

R

Ridout, M. S. 2004. An Empirical Model for Underdispersed Count Data. ***Statistical Modelling***, 4: 77-89.

Rogers, E. M. 1962. ***Diffusion of Innovations***. New York: The Free Press.

Rosenberg, N. 1976. ***Perspectives on Technology***. Cambridge: Cambridge University Press.

Rosenberg, N. 1982. ***Inside the Black Box: Technology and Economics***. Cambridge: Cambridge University Press.

Rosenberg, N. 1996. Uncertainty and Technological Change. In R. Landau, T. Taylor, & G. Wright (Eds.), ***The Mosaic of Economic Growth***. Stanford, CA: Stanford University Press.

Rosenkopf, L., & Nerkar, A. 1999. On the Complexity of Technological Evolution: Exploring Coevolution within and across Hierarchical Levels in Optical Disc Technology. In J. A. C. Baum, & B. McKelvey (Eds.), ***Variations in Organization Science: In Honor or Donald T. Campbell***: 169-183. London: Sage.

Rosenkopf, L., & Nerkar, A. 2001. Beyond Local Search: Boundary-Spanning, Exploration, and Impact in the Optical Disk Industry. ***Strategic Management Journal***, 22: 287-306.

Rosenkopf, L., & Tushman, M. L. 1994. The Coevolution of Technology and Organization. In J. A. C. Baum, & J. V. Singh (Eds.), ***Evolutionary Dynamics of Organizations***: 403-424. Oxford: Oxford University Press.

Ruef, M. 2000. The Emergence of Organizational Forms: A Community Ecology Approach. ***American Journal of Sociology***, 106: 658-714.

S

Sahal, D. 1981. Alternative Conceptions of Technology. ***Research Policy***, 10: 2-24.

Sahal, D. 1985. Technological Guideposts and Innovation Avenues. ***Research Policy***, 14: 61.

Sasisekharan, R. 2005. Bioengineering at Mit: Building Bridges between the Sciences, Engineering and Health Care (Part Two). ***MIT Lecture***Available online at MIT World.

Schulz, M. 1998. Limits to Bureaucratic Growth: The Density Dependence of Organizational Rule Births. ***Administrative Science Quarterly***, 43: 845-876.

Schumpeter, J. A. 1934. ***The Theory of Economic Development***. Cambridge, MA: Harvard University Press.

Schumpeter, J. A. 1939. ***Business Cycles***. New York: McGraw-Hill.

Schumpeter, J. A. 1943. ***Capitalism, Socialism, and Democracy***. London: George Allen and Unwin.

Shannon, C. E. 1948. A Mathematical Theory of Communication. ***Bell System Technical Journal***, 27: 379-423.

Shrum, W., & Wuthnow, R. 1988. Reputational Status of Organizations in Technical Systems. ***American Journal of Sociology***, 93: 882-912.

Simmel. 1950. ***The Sociology of George Simmel***: The Free Press.

Simon, H. A. 1957. ***Herbert A. Simon. Models of Man: Social and Rational***. New York: John Wiley and Sons, Inc.

Simon, H. A. 1962. The Architecture of Complexity. ***Proceedings of the American Philosophical Society***, 106: 467-482.

Simon, H. A. 1982. ***Models of Bounded Rationality***. Cambridge, Massachussets: MIT Press.

Smookler, J. 1966. ***Invention and Economic Growth***. Cambridge, MA: Harvard University Press.

Solow, A., & Polaski, S. 1994. Measuring Biological Diversity. ***Environmental and Ecological Statistics***, 1: 95-107.

Sorensen, J. B., & Stuart, T. E. 2000. Aging, Obsolescence, and Organizational Innovation. ***Administrative Science Quarterly***, 45: 81-112.

Sorger, P. 2004. Computational and Systems Biology at Mit. ***Symposium on Systems Biology at MIT***Available online at MIT World.

Spence, M. 1984. Cost Reduction, Competition, and Industry Performance. ***Econometrica***, 52: 101-121.

Stinchcombe, A. L. 1965. Social Structure and Organizations. In J. G. March (Ed.), ***Handbook of Organization***: 142-193. Chicago: Rand McNally.

Stirling, A. 2007. A General Framework for Analyzing Diversity in Science, Technology, and Society: SPRU Electronic Working Paper Series, number 156: Science Policy Research Unit, University of Sussex.

Stolberg, S. G. 2007. Bush Vetoes Measure on Stem Cell Research, ***New York Times***. New York.

Stuart, T. E. 1998. Network Positions and Propensities to Collaborate: An Investigation of Strategic Alliance Formation in a High-Technology Industry. ***Administrative Science Quarterly***, 43: 668-698.

Stuart, T. E. 1999. A Structural Perspective on Organizational Innovation. ***Industrial and Corporate Change***, 8: 745-775.

Stuart, T. E. 2000. Interorganizational Alliances and the Performance of Firms: A Study of Growth and Innovation Rates in a High-Technology Industry. ***Strategic Management Journal***, 21: 791-811.

T

Termeer, H. 2002. Biotechnology - Will It Create a New Industry? ***MIT Lecture***Available online at MIT World.

Thoma, G., & Torrisi, S. 2007. Creating Powerful Indicators for Innovation Studies with Approximate Matching Algorithms. A Test Based on Patstat and Amadeus Databases. ***Cespri working paper series***.

Trajtenberg, M. 1990. A Penny for Your Quotes - Patent Citations and the Value of Innovations. ***Rand Journal of Economics***, 21: 172-187.

Tushman, M. L., & Anderson, P. 1986. Technological Discontinuities and Organizational Environments. ***Administrative Science Quarterly***, 31: 439-465.

Tushman, M. L., & Murmann, J. P. 1998. Dominant Designs, Technology Cycles, and Organizational Outcomes. ***Research in Organizational Behavior, Vol 20, 1998***, 20: 231-266.

Tushman, M. L., & Nelson, R. R. 1990. Technology, Organizations, and Innovation - Introduction. ***Administrative Science Quarterly***, 35: 1-8.

Tushman, M. L., & Romanelli, E. 1985. Organizational Evolution: A Metamorphosis Model of Convergence and Reorientation. ***Research in Organizational Behavior***, 7: 171-222.

Tversky, A. 1977. Features of Similarity. ***Psychological Review***, 84: 327-352.

U

Utterback, J. M., & Abbernathy, W. J. 1975. A Dynamic Model of Product and Process Innovation. ***Omega***, 3: 639-656.

Utterback, J. M., & Suárez, F. F. 1993. Innovation, Competition, and Industry Structure. ***Research Policy***, 22: 1-21.

V

Van den Bosch, F. A. J., Volberda, H. W., & de Boer, M. 1999. Coevolution of Firm Absorptive Capacity and Knowledge Environment: Organizational Forms and Combinative Capabilities. ***Organization Science***, 10: 551-568.

Van Looy, B., Debackere, K., Martens, T., & Bouwen, R. 2005. Exploring Requisites and Antecedents of Continuous Innovation, ***INCENTIM working paper***: Catholic University of Leuven.

Van Looy, B., Magerman, T., & Debackere, K. 2006. Developing Technology in the Vicinity of Science: An Examination of the Relationship between Science Intensity (of Patents) and Technological Productivity within the Field of Biotechnology. Available at Ssrn: Http://Ssrn.Com/Abstract=874918.

van Santen, R. A., Khoe, G. D., & Vermeer, B. 2007. ***The Thinking Pill***: Nieuw Amsterdam Publishers.

Venter, C. 2008. New Ideas, New Fuels: Vraig Venture at the Oxonian. New York: Fora.tv.

Vermeulen, I., & Bruggeman, J. 2001. The Logic of Organizational Markets: Thinking through Resource Partitioning Theory. ***Computational & Mathematical Organization Theory***, 7: 87-111.

Verspagen, B. 2005. ***Mapping Technological Trajectories as Patent Citation Networks: A Study on the History of Fuel Cells***. Paper presented at the Structural change, employment, productivity and growth: Issues and perspectives, Fondation des Treiles.

W

Wade, J. 1995. Dynamics of Organizational Communities and Technological Bandwagons - an Empirical-Investigation of Community Evolution in the Microprocessor Market. ***Strategic Management Journal***, 16: 111-133.

Wasserman, S., & Faust, K. 1994. ***Social Network Analysis: Methods and Applications***. Cambridge: Cambridge University Press.

Weick, K. 1979. ***Social Psychology Oforganizing***. Reading, MA: Addison-Wesley.

Weitzman, M. L. 1992. On Diversity. ***Quarterly Journal of Economics***, 107: 363-405.

Weitzman, M. L. 1996. Hybridizing Growth Theory. ***American Economic Review***, 86: 207-212.

Winter, S. G. 1984. Schumpeterian Competition in Alternative Technological Regimes. ***Journal of Economic Behavior & Organization***, 5: 287-320.

Winter, S. G. 2008. Scaling Heuristics Shape Technology! Should Economic Theory Take Notice? ***Industrial and Corporate Change***, 17: 513-531.

van Witteloostuijn, A. 1990. ***Rationality, Competition and Evolution: Entry (Deterrence) in Dynamic Barrier Market Theory***. University of Limburg, Maastricht.

van Witteloostuijn, A. 1994. ***Laat Duizend Bloemen Bloeien: Tolerentie in En Rond Organisaties***. Schoonhoven: Academic Service.

van Witteloostuijn, A. 2003. The Ecology of Law. ***International Journal of the Sociology of Law***, 31: 55-67.

van Witteloostuijn, A., & Boone, C. 2006. A Resource-Based Theory of Market Structure and Organizational Form. ***Academy of Management Review***, 31: 409-426.

van Witteloostuijn, A., & de Jong, G. 2009. An Ecology of National Rule Birth: A Longitudinal Study of Dutch Higher Educational Law 1960-2004. ***Journal of Public Administration research and Theory***.

van Witteloostuijn, A., & de Jong, G. 2007. The Evolution of Higher Education Rules: Evidence for an Ecology of Law. ***International Review for Administrative Sciences***, 73: 235-255.

Y

Young, P. 1993. Technological Growth-Curves - a Competition of Forecasting Models. ***Technological Forecasting and Social Change***, 44: 375-389.

Z

Zahra, S. A., & George, G. 2002. Absorptive Capacity: A Review, Reconceptualization, and Extension. ***Academy of Management Review***, 27: 185-203.

Zucker, L. G. 1989. Combining Institutional Theory and Population Ecology: No Legitimacy, No History. ***American Sociological Review***, 54: 524-541.

Summary

In this day and age, arguing that technology is a powerful force that drives many economic processes is like preaching to the choir. Nevertheless, despite the widespread realization of the important role of technology in our modern day society, an intimate understanding of the process of technological change is still lacking. This study seeks to provide more insight into the concept of technological change by characterizing it as a socio-cultural evolutionary process of variation, selection and retention. According to this logic, variety (or novelty) is created by (random or non-random) mutations (i.e., organizations and individuals that (re-) combine existing components in novel ways). This variety is subsequently selected out by the stakeholders in the environment, such as individuals, organizations, and institutions. In other words, the variety is then retained in the structural characteristics of the environment, commonly referred to as organizational routines and technological paradigms. Finally, these structural characteristics subsequently provide the context in/from which new mutations (or variations) are created. From there, the cycle can be repeated.

Because, nowadays, technology is mostly developed in an organizational context, the appropriate place to study technology and technological change is in the context of organization science, which is an academic discipline that studies all facets of organization. Even though technology deserves a central role in any organization theory, technology has not yet penetrated fully the domain of organization science. The only domain in which technology has a central role is within evolutionary economics, a school of economic thought that was influenced by evolutionary biology. Even though evolutionary economics has surely added much to our understanding of the process of technological change, in our view, this school of thought mainly concentrates its attention on idiosyncratic accounts of variety creation and their subsequent selection by the environment. Much less attention has been attributed to how the selection environment (or the structural characteristics thereof) determines the variety creation. Consequently, insights from organizational ecology, which has its center of gravity at the selection environment, can add value over and above the ones originating from evolutionary economics. The key source of inspiration of organizational ecology is bio-ecology, which makes it evolutionary economics' counterpart in sociology.

In this study, we therefore seek to close the evolutionary circle by developing a structural or ecological perspective of technological change. After all, holding both links between variety and selection in focus at the same time (i.e., how variety is selected by the environment, and how the selection environment facilitates and constrains the creation of variety) provides for a truly evolutionary model of technological change. Accordingly, we define our research objective as follows:

Research objective: *To develop an ecology of technology in organization science.*

Because this objective is rather vague and abstract, we formulate several research questions to provide more direction in our quest to fulfill our objective. We formulate our first research question as follows.

Research question 1*: What is the importance of biotechnology?*

Providing an answer to this research question is the subject of Chapter 2. As a means of introducing biotechnology, we first describe biotechnology's central dogma (i.e., DNA as the building block of life). Moreover, we provide a timeline to get a certain feel of the history and evolution of biotechnology, and list numerous socio-economic trends to get an idea of the importance of biotechnology in society. These trends clearly illustrate that biotechnology drives important social and economic events. Next, we evaluate biotechnology's position in the overall technological landscape. Our main finding is that, despite its sharply increasing societal and economic importance, biotechnology still has not yet conquered a place in the technological core of our society. Reviewing the developments within synthetic biology (in this domain, complex systems are designed by (re-)combining DNA into biological parts that represent biological functions and, as such, is the domain where all aspects of biotechnology come together), it becomes clear that biotechnology as a whole is not yet in the growth stage of technological convergence that is characterized by a stable configuration of component technologies (i.e., a dominant design). Moreover, on the basis of the future expectations of experts, we conclude that biotechnology is a strategic technology that is nowhere near its peak influence, and that we can expect the importance to increase even further over the coming years. Obviously, whether biotechnology can deliver on its promise and materialize the expectations of insiders is not certain. Even when biotechnology delivers on only a small part of the promise, though, its impact will already be gigantic. For example, consider the fact that, in a 2007 interview, Craig Venter – who is one of the most well-renowned biotechnologists today – said that, in 20 years time, synthetic genomics is going to become the standard for making anything (Aldhous, 2007). So, in conclusion, biotechnology is a technology that is still emerging and does yet not display a stable and predictable pattern of growth that characterizes mature (i.e., non-emerging) technologies. Our next research question thus is as follows.

Research question 2*: How to study the growth of an emerging technology?*

In Chapter 3, on the basis of ecological insights and principles, we develop a structural or systemic view towards technology, and hereby take into explicit account the embedded nature of technology. That is, we propose that it adds value to view technology as a system composed of a set of interdependent components (or subsystems). More specifically, by relying on density dependence theory from organizational ecology, we effectively develop a multilevel framework that can be used to empirically study emerging technologies. Moreover, we employ the concept of the technological niche from organizational ecology, with its associated dimensions of crowding (associated with processes of competition) and status (associated with processes of legitimation), and add diversity as a key dimension. Through sophisticated multivariate analysis of biotechnology patents from the United States Patent and Trademark Office (USPTO), we validate this model, which we label the 'ecology of technology'. However, we also discover some anomalies, which point to the limitations of our model, the most important being its rather static nature. Because emerging technologies are characterized by fluid patterns of growth, a static model is a severe misrepresentation of the evolution of emerging technologies. Our next research question naturally follows from this.

Research question 3: *How to study the evolution of an emerging technology?*

On the basis of insights from evolutionary economics, Chapter 4 distinguishes between two stages of technological development, namely the stages of divergence and convergence (that connect nicely with the seed and growth stage of life cycle theory). The focal element is what is generally referred to as the deep structure (in the context of technology also commonly referred to as a dominant design) that facilitates cumulative changes by reducing uncertainty and enabling specialization and integration through standardization. The stage of divergence is characterized by the absence of a deep structure, while the stage of convergence is characterized by its presence. So, in the latter stage, there is a relatively stable configuration of the system's component technologies that results in relatively stable and predictable patterns of growth. On the basis of these insights, we adapt our multi-level model to identify these different stages of development at the component level. More specifically, if there is a mutualistic relationship between a component and the system (i.e., if system density contributes positively to component entry), the component is argued to have a dominant design. As we are dealing with an emerging technology, our main interest lies in the transition from the initial seed stage of technological divergence (i.e., the absence of a deep structure) to a growth stage of technological convergence (i.e., the existence of a deep structure), or the creation of a deep structure. This means that we do not take into account the revolutionary transition from a stage of convergence into divergence (i.e., the maturity and decline stage in life cycle theory).

Not only do we refine our predictions regarding the effects of our existing dimensions (i.e., multilevel density dependence, crowding, status, and focal diversity), but, by further taking into account the lineage of technology, we refine our dimension of diversity by adding antecedent and descendant diversity as additional dimensions to the technological niche. This results in an intricate model that can be used to study the growth and evolution of an emerging technology. We demonstrate this by an empirical investigation of biotechnology patents from the USPTO and hereby provide further support for our 'ecology of technology'. In the light of our research objective, before we answer the question of what the precise consequences are for organizations, we ask ourselves how we can effectively integrate our findings at the organizational level of analysis. We thus formulate our next research question accordingly.

Research question 4: *How can we integrate technology into the theory of the organization specific technological niche?*

In Chapter 5, we use a process of logical formalization to represent the theory of the organization-specific technological niche in a formal logical language. The reason for doing so is threefold. First, this forces us to explicate all underlying assumptions and to remove any inconsistencies to make the argument logically sound. Second, this requires us to supplement the theory so that it is complete, without missing elements. Third and finally, it results in a logically sound and complete theory fragment ready for extension by integrating the insights from the study of the evolution of technology. We choose non-monotonic logic as the language in which we represent our arguments because non-monotonic logic is better suited for theory building, and this connects better to the current wave of formalization in non-monotonic logic in organizational ecology. On the basis of this analysis, we already make two important theoretical extensions. First, by distinguishing between crowding in technological and market space, we tie technological crowding to both competition and legitimation. To be precise, technological crowding results in competition mainly if the crowding organization is a competitor of the focal organization. Second, uncertainty mediates the relationship between the perceived and actual technological quality of the organization. More specifically, under uncertainty, the actual quality of an organization's technology cannot be readily observed so that resource controllers have to rely on status (i.e., historic technological quality) instead. With this formalized, logically sound and complete theory fragment in hand, we can turn to the question of the organizational consequences. We thus pose our next research question as follows.

Research question 5: *What are the consequences of integrating several technological insights into the theory of the organization-specific technological niche?*

In Chapter 6, we integrate four technological insights from Chapters 3 and 4 into our formalized theory fragment from the previous chapter. These insights are: (1) multiple technological domains exist that have (2) different stages of development, (3) different levels of uncertainty, and (4) different growth rates. On the basis of these four insights, we extend the theory of the organization-specific technological niche considerably. For crowding, we demonstrate that the effect of crowding is not only conditional upon the identity of the other organization, but also on the stage of technological development. We also add non-crowding to the mix. Regarding the effect of (non-)crowding, in the stage of divergence, multiple competing design configurations exist, and crowding (non-crowding) increases (decreases) the competitiveness of the supported design configuration, having a legitimating (competition) effect. In contrast, in the stage of convergence, crowding (non-crowding) loses its legitimating (competition) function and results in competitive (legitimation) pressure. For status, the most important consequences are that: (1) status is domain dependent, and (2) its effect is dependent upon the stage of technological development (i.e., the effect of status is higher in the stage of divergence). We also add two additional dimensions, which are (1) technological opportunities (that can be represented by the growth rate of the domain), and (2) technological diversity (measured by the distribution of activities over alternative domains). By operationalizing performance as a two-dimensional vector, we suggest that the dimensions of the technological niche are related to different performance measures in distinct temporal relationships. However, even though this theoretical extension is certainly valuable, the subsequent question is whether these extensions hold when subjected to advanced empirical tests. We therefore formulate our next research question as follows

Research question 6: *Can we find proof for our extended theory of the organization-specific technological niche?*

In Chapter 7, we empirically test several of our theoretical extensions of the organization-specific technological niche. Our dependent variable is biotechnology innovation (i.e., the number of biotechnology patents). Through a sophisticated empirical analysis, we find strong support for our extended theory. However, we also encounter some inconsistencies and anomalies. This seems to connect to the fact that processes of competition and legitimation are more appropriately defined at lower levels of analysis (i.e., at the component instead of at the system level). Moreover, due to the dual role of a direct technological tie (i.e., it can have both a competing and a legitimating function) that forms the basis for our measure of status, status is better defined at the component level of analysis. In contrast, biotechnological quality can be aggregated to the system level without losing significance. We thus find strong support for this dimension.

Furthermore, we also clearly demonstrate the importance of taking into account the different dimensions of technological diversity (i.e., antecedent, focal, and descendant), with a vital role for antecedent diversity, which logically connects with the notion of absorptive capacity. The subsequent question is what this means for the broader academic debate regarding the (co-)evolution of technology and organization. We formulate our next research question accordingly.

Research question 7*: What are the implications for the study of the (co-)evolution of technology and organization?*

In the final chapter of this dissertation, we start by stating the main contribution of this dissertation, which is that we develop a dynamic multilevel model that can be used to empirically study the evolution of an emerging technology. As this model is based on the assumption that technology can effectively be studied as a system composed of an interacting set of components, we pay explicit attention to the embedded nature of technology. Hence, when studying the evolution of technology, it is inappropriate to focus on a single level of analysis and using a multilevel perspective adds value over and above any single level study. That is, technology (e.g., biotechnology) is composed of a set of technological components (e.g., biotechnology's component technologies) while, at the same time, being embedded in a larger technological system (i.e., technological landscape). It is precisely this multilevel nature of technology that gives it the potential to close part of the chasm in the debate between organizational adaptation (i.e., the dominant perspective in evolutionary economics) and environmental selection (i.e., the dominant perspective in organizational ecology). More specifically, by defining technology at different levels of analysis (e.g., invention, component, system, and landscape), it is possible to tie the evolution of technology to the evolution of organization at different levels of analysis (i.e., individual organization, population of organizations, community, and society). This enables studying the evolution of technology and organization in unison, and thus provides the basis for a co-evolutionary model of technology and organization. Employing a multilevel perspective to both technology and organization at the same time, and defining technology and organization as nested hierarchies tied together at multiple levels of analysis, effectively allows an analyzes of how stable configurations travels upwards in this hierarchy. After all, "it is the information about stable configurations […] that guides the process of evolution" (Simon, 1952: 473).

About the author

Ad van den Oord was born on February 20, 1972. In 1990, he started his Bachelor of Architectural Engineering and Economics at the Avans University of Applied Sciences in 's-Hertogenbosch (the Netherlands). After graduation, in 1995, he studied International Business at Maastricht University (the Netherlands). During the academic year 1998-1999, in cooperation with KMPG Alliances (Amstelveen, the Netherlands), he wrote his Master's thesis on Alliance Networks. During the final part of his study period, he did an internship at the International Center for Alliances, Networks, and Strategic Innovation (ICANSI) in Silicon Valley (Santa Clara, USA), where he translated many ideas and concepts from his Master's thesis into concrete products and services. One of these products, called the Alliance Information System, was even spun-off into a new business venture called the Centre for Global Corporate Positioning (CGCP, the Netherlands).

After graduating in December 1999, he started working as a researcher at Eindhoven University of Technology (the Netherlands). However, in response to the opportunities created during his internship at ICANSI, he co-founded The Brillianz Group (Eindhoven, the Netherlands) to materialize upon these opportunities. During this period, he was a jack-of-all-trades and, amongst others, he managed The Brillianz Group, he managed the development process of the Alliance Information System at CGCP, he was a contract teacher at Compu'Train (Utrecht, the Netherlands) and Eduvision (Arnhem, the Netherlands), he was involved in the development of several new internet business concepts (e.g., Beurz.nl which was later successfully taken over by IEX.nl and is now better known as Guruwatch.nl), he designed and developed numerous websites, and was a contract researcher at Eindhoven University of Technology.

Towards the end of 2002, due to his academic aspirations, Ad started working full-time at Eindhoven University of Technology again. However, it was not until the beginning of 2004 that his ideas regarding his dissertational research really started to solidify. During this period, he worked on his PhD next to his tasks as a researcher. As of January 2007, he formally became a PhD student to focus all his attention on his dissertation and to enable his stay as a visiting PhD student at the University of Antwerp (Belgium). As of June 2009, Ad works as a researcher at the Antwerp Centre for Evolutionary Demography, which is a center of excellence at the department of management of the University of Antwerp that has been established by Prof. Arjen van Witteloostuijn through the Odysseus program of the Flemish Science Foundation (FWO).