The Ecology of Technology

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Abstract 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 (or set) of related of inventions. More specifically, by employing a population perspective to technology, we aim to determine to what extent the pattern of technological growth can be attributed to the structural characteristics of the technology itself. Through an empirical investigation of patent data in the biotechnology industry, we show that a technology's internal (i.e., density and diversity) and external (i.e., crowding and status) characteristics have a significant effect on its growth rate. Finally, we discuss the implication of our findings for the development of what we coin the ecology of technology.
Key words population, ecology, technology, technological growth

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 individual, groups, and organizations (Barnett, 1990; Baum & Powell, 1995; Duysters, 1995; Lawless & Anderson, 1996; Marx, 1906; Saviotti, 2008; Schumpeter, 1943; Suarez & Utterback, 1995; Tushman & Nelson, 1990; Utterback & Suarez, 1993). 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 paper, 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 the 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 paper is to move beyond a descriptive account of technological change and 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 employing a population perspective of technology, we aim to determine to what extent the pattern of technological growth can be attributed to the structural characteristics of the technology itself, defined as a population or set of related inventions. 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. Here, we define technological niches as populations of related inventions and the technological ties to and from these inventions. So, our key aim is to develop a theory of why growth rates differ across technologies 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 the technological niche – i.e., characteristics of the population of related inventions – and the way in which this niche is embedded in its wider technological environment – i.e., technological ties to and from these inventions. 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 paper makes is twofold. First and foremost, to come to a better understanding of the process of technological growth, we argue that a population perspective toward technology is warranted. To do so, we can nicely bring in insights from organizational ecology. Second, these technological growth patterns are to a large extent determined by the structural characteristics of the technological niche. 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.

The major contribution of this paper is, therefore, that we further our understanding of the process of endogenous technological growth by employing notions from organizational ecology, suggesting a new approach that may be coined the ecology of technology. In doing so, we extend the notion of the technological niche, which can provide the basis for further studies into processes of endogenous technological change, or act as an explanatory variable in studies of organizational or industrial change. More specifically, we add internal technological diversity as a key structural feature of the technological niche, and illustrate the importance of adding a measure of technological diversity as an independent variable 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.

The structure of this paper is as follows. Section 2 describes the process of endogenous technological growth and we will develop our theoretical model and associated hypotheses in Section 3. In Section 4, we will elaborate on the empirical setting of our study, introduce our empirical measures, and explain our estimation methods. Section 5 will present the results of our empirical analyses. And finally, in Section 6, the findings will be discussed in relation to our theory and the broader literature.

2 Endogenous Technological Growth

In the previous century, Schumpeter (1943) presented an evolutionary theory on 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 et al., 2001; Henderson & Clark, 1990; Nelson & Winter, 1982). In this paper, 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. This logic is demonstrated in figure 1 below.

Figure 1 Technological lineage

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 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 nicely bring in insights from organizational ecology, a prominent sociological theory on the evolution of populations of organizations, and produce value added.

The phenomenon of technological growth spans multiple levels of analysis, and developing a multilevel model adds insights and depth well beyond any single level of analysis (Tushman et al., 1990). So, therefore, in analogy to Ruef (2000), we define a technological community (e.g., biotechnology) as a bounded set of technological forms (e.g., genetic engineering or viral technology) with a related identity. Here, technological form refers to a community's component technology, and is defined as a population (or set) of related inventions. This multilevel model is displayed graphically in figure 2 below.

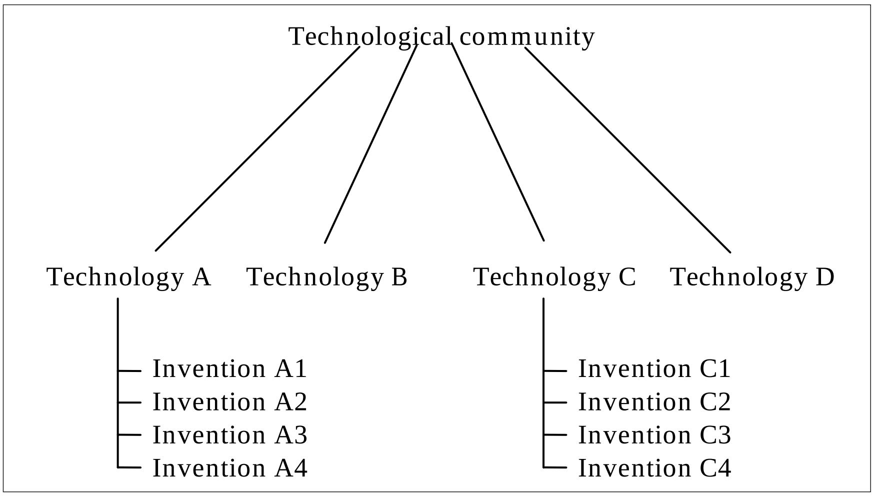

Figure 2 A multilevel model of technology

Hence, we study the entry of inventions into technological forms (i.e., the growth of component technologies). These forms are embedded in a larger technological community and, in turn, this community (e.g., biotechnology) is embedded in a larger technological environment with connections to and from alternative communities (e.g., semiconductors, chemicals, and pharmaceuticals), see figure 3. 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. As we will argue in greater detail below, this process of endogenous technological growth is determined by the 'ecological' characteristics of the technological niche – i.e., characteristics of the technological form – and the way in which the niche is embedded in its wider technological environment – i.e., technological ties to and from this technological form. This makes the concept of a technological niche useful for the purpose of our study as it points to the important role of the <u>structural</u> characteristics <u>internal</u> to technology in driving the process of technological growth.

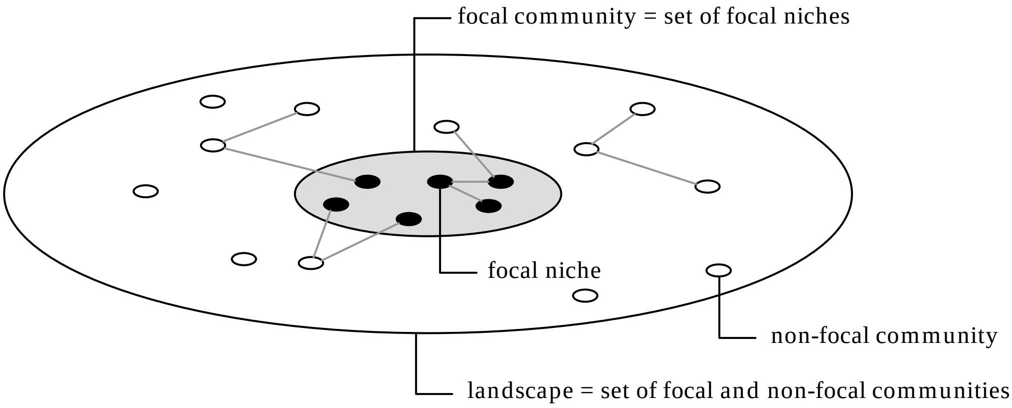

Figure 3 Technological landscape Containing Focal and Non-focal Communities

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 (Baum & Singh, 1994; Dobrev, Kim, & Carroll, 2002, 2003; Dobrev, Kim, & Hannan, 2001; Freeman & Hannan, 1983; Hannan, Carroll, & Polos, 2003; Lawless et al., 1996; Podolny et al., 1995; Podolny, Stuart, & Hannan, 1996) and theoretical studies (Hannan et al., 2003; Hannan, Pólos, & Carroll, 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 technological forms, or technological niches.

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. The authors defined the technological niche as the relational context of an invention that co-evolves with technological change. In cooperation with Michael Hannan, the authors (Podolny et al., 1996) subsequently developed the organization-specific technological niche 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 their notion of the technological niche. However, as mentioned, instead of applying the niche to individual inventions or to an organization's inventions, we further extend the concept of the technological niche by applying it at the level of a technological form (e.g., genetic engineering), or a population of (more or less) related inventions. We thus define the technological niche as a technological form and the technological ties to and from this form. This implies that we use the terms technological niche and form interchangeably in the current paper. So, our key dependent variable is growth of the technological form (or niche) as reflected in entry by new inventions, coined niche entry.

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 niche itself, (2) the embeddedness of the niche in the technological network or broader environment, and (3) the characteristics of the organizations populating the niche. As argued, the aim of this study is to develop a model of endogenous technological changes. 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.

3.1 Niche density

Researchers have observed a characteristic pattern of evolution of diverse organizational populations: initially, 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 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 et al., 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 et al., 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 et al., 1989). Here, 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, because the capacity of a form to mobilize resources is to a large extend dependent on the extent to which (extremely skeptical) resource controllers take the form for granted (Aldrich & Fiol, 1994; Carroll et al., 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". Hence, legitimation processes 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 et al., 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 et al., 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 & Jong, 2007) and organizational rules (March, Schulz, & Shou, 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, it is commonly known that the growth of technology also displays characteristic patterns (Dosi, 1988), and the existence of S-shaped growth curves in technology has recently been empirically validated (Andersen, 1999). 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 et al., 1997). After all, there are also marked differences between technologies and organizations. This implies that we should carefully consider the extent to which processes of competition and legitimation operate in technological populations.

Here, we anticipate that processes of legitimation also operate in technological populations. After all, it is widely acknowledged that technologies need to be legitimized (Aldrich et al., 1994; Anderson & Tushman, 1990; Dosi, 1988; Duysters, 1995; Nooteboom, 2000; Zucker, 1989). According to Meyer and Rowan (1977), technologies are institutionalized and become a taken-for-granted means to accomplish organizational ends. Hence, organizations adopt technology to enhance their legitimacy (Dimaggio & Powell, 1983). This is especially in the formative stage of a technological form, 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). So, analogous to the acceptance of a new organizational form by society, legitimacy of a new technology increases with the number technological inventions. Hence, the denser the niche, the better understood the new technology becomes and the more it is taken-for-granted, which enhances further this niche's growth. Thus, at low levels of niche density, we expect to find a positive association between niche density and niche entry.

Regarding the existence of competitive processes, ideas and innovations compete with one another for the attraction of resources and attention (Basalla, 1988; Podolny et al., 1995). More specifically, 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. After all, a firm's research budget or an investor's capital is not unlimited. This implies that inventions (are used to) compete for these scarce resources. As noted, increasing density increases the number of indirect competitive linkages exponentially. So, processes of competition dominate the relationship at high levels of density. This implies that, at high levels of density, we expect a negative association between niche density and niche entry. Our first hypothesis thus becomes as follows.

Hypothesis 1A: Focal niche density is first positively and later negatively associated with the growth rate of the focal niche, implying a non-monotonic inverted U-shaped effect of focal niche density on focal niche entry.

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 multidimensional construct and cannot be adequately represented by a measure as crude as population density (Baum et al., 1995; Zucker, 1989). These contenders argue that population evolution is dependent on idiosyncratic events (e.g., legislative changes or overt political support) which are largely ignored when merely studying population numbers. Ecologists have responded by arguing 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). We also have the aim to develop a general theory of technological growth and thus choose to follow the ecologist approach in this matter and control for peculiar events.

On the other hand, the competitive aspect of the theory has also been challenged. Here, 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). Recent research indicates that competitive processes are highly localized, because, on the one hand, competition is tied to material resources (i.e., plants, products, and people), and therefore hampered by spatial and geographic boundaries (Baum et al., 2006; Carroll et al., 2000; Lomi, 1995). On the other hand, legitimation is tied to information, which flows more freely and and is therefore hampered less by boundaries. So, legitimation processes are argued to operate more broadly than do competitive processes (Carroll et al., 2000). This observation is duly noted by ecologists and provides fertile grounds for extending the density dependence model. One of the proposed extensions is employing multilevel 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 et al., 2000), but also by technological boundaries. That is, we claim that technology also localizes competitive processes, and that processes of legitimation operate on a broader technological scale. Hence, we expect density within the entire technological community to be tied to processes of legitimation, but not to processes of competition. Our next hypothesis can thus be formulated as follows.

Hypothesis 1B: Community (or system-wide) density is positively associated with focal niche entry.

3.2 Niche diversity

As previously noted, the competitive element of the density dependence argument has been criticized because it assumes that populations are homogeneous (i.e., that diffuse competition affects each member equally). We have also stipulated that recent research suggests that population segments respond heterogeneously to competitive and institutional processes. This means that population heterogeneity is important, and we need to consider the extent to which sub-forms (or population segments) exist for a number of reasons. First, according to Durkheim's (1933), that 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 decreases. So, according to this argument, as the rate of entry is tied to the competitive intensity within the population, we expect niche entry to increase with niche diversity. Second, diversity provides flexibility in uncertain environment and mitigates lock-in (Stirling, 2007). Because technological developments within biotechnology are of a highly uncertain nature, flexibility becomes highly important by providing alternative directions for future development. As such, diversity is indicative of niche width, and increasing the diversity of the niche increases its potential applicability in the wider environment, and is thus appealing to a wider variety of stakeholders in that environment. Third and finally, as we conceive technological change as a process recombination, increasing the number of sub-forms or segments in the niche increases the opportunities for their (re-) combination, yielding further opportunities for new combinations, and so on and so forth. Hence, we expect diversity to have a positive effect on niche entry because it (1) reduces competition, (2) mitigates lock-in by increasing flexibility, and (3) increases recombinatory potential. We thus formulate our next hypothesis as follows.

Hypothesis 2: Focal niche (or form) diversity is positively associated with focal niche entry.

3.3 Niche crowding

In ecological studies, niche crowding or overlap is commonly equated with competition, as it implies a similarity in resource requirements (Baum & Mezias, 1992; Dobrev et al., 2001; Hannan & Freeman, 1977; Hannan et al., 1989; Hannan et al., 2007; Podolny et al., 1996), and builds upon the notion that the potential of competition is directly proportional to the overlap of resource bases (Baum et al., 1994). In these studies, population members usually consist of organizations. In the current paper, however, we deviate from this tradition, and view our technological forms (or niches) as members. Moreover, we define the technological environment as a resource space, and claim that an overlap of the niches of our technological forms increases the competitive potential between them. Hence, increasing the extent to which two focal technological forms (e.g., forms A and B) build upon the same alternate forms (e.g., forms C and D), increases the potential for competition between the focal forms (i.e., forms A and B). So, here, we argue that, just like competition is stronger among structurally equivalent organizations (Burt, 1992), competition is stronger between structurally equivalent technologies (i.e., that use the same component technologies or technological forms in their recombination process). Consequently, competitive processes can not only be observed within (as argued under niche density) but also between technological forms. As a result, we expect to find a negative association between niche crowding and niche entry.

Conversely, the received literature also allows for positive spillovers or externalities of niche crowding. Regarding this positive effect, according to the extant literature, crowding is argued to provide knowledge and reputation spillovers (Fleming & Sorenson, 2004; Jaffe, 1986; Levin, 1988), enables a sharing of infrastructure and creation of economies of standardization (Baum & Haveman, 1997; Wade, 1995), and facilitates vicarious learning (Delacroix & Rao, 1994). This mutualistic relationship has been validated empirically in several studies (Boone, Wezel, & van Witteloostuijn, 2004; Fleming, 2001; Jaffe, 1986; Levin, 1988; Pontikes, 2007; Spence, 1984; Stuart, 1999). Accordingly, we also need to accommodate for a positive effect of niche crowding. After all, the more common the technological components (or forms) that are used in the recombination process, the more common is the knowledge that exists about these components, which greatly facilitates the recombination process. Particularly well-established components might even be supported by a knowledge infrastructure (e.g., books, educational courses and programs), which can lead to economies of standardization and vicarious learning. As such, we also expect crowding to be positively associated with niche entry, due to positive spillover and network externalities.

When allowing for both a positive and a negative effect of niche crowding on niche entry, an important question becomes: How can we accommodate for both a positive and a negative association between niche crowding and niche entry? The answer to this question lies in a recent study performed by Pontikes (2007). In an empirical investigation of the computer study, she effectively illustrates technological crowding to results in competition only when organizations are competitors. She therefore proposes a distinction between competitor and non-competitor crowding to accommodate for the opposite effects of crowding. As stated earlier, we focus on technology only and abstract from the role of the organization. This implies that we also abstract from the markets in which organizations are active, which makes this distinction rather difficult. However, by adopting a similar logic, we can also make a distinction between crowding by competing and non-competing technologies. So, the question becomes how to make a distinction between competing and non-competing technologies?

Here, guidance is provided by organizational ecology's localized competition postulate. We have explained before that the more similar focal is to competitors, the greater the intensity of competition that focal will experience (Baum et al., 1992; Hannan et al., 1977, 1989). According to Hannan and Feeman (1989), competition is stronger between organizations within a given 'niche'. So, organizations that are more local (i.e., more similar or close to one another) are more probable to vie for the same pool of resources (Barnett, 1997). Even though this concept has mainly been applied to organizations in geographical or (resource) market space, we have already argued that it can also be nicely used when studying technological forms in a technological space. So, again, we argue that competitive processes within populations of inventions are hampered by technological boundaries (or technological distance). Hence, we argue that within technological populations, competitive processes operate on a more local level. Regarding the positive externalities or spillovers, we expect them to operate both at the global as well as at the local level. However, we hypothesize that the local level is dominated by the stronger competitive processes.

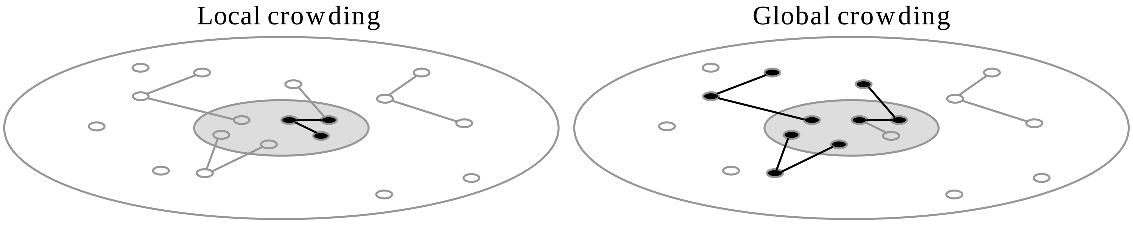

Figure 4 Local vs. Global Crowding

So, we propose to make a distinction between, on the one hand, crowding of our focal technological forms among themselves (i.e., local crowding), and, on the other hand, crowding of our focal niches with non-focal forms (or niches) in the environment (i.e., global crowding), see figure 4. Our next hypotheses can now be formulated as follows.

Hypothesis 3A: Local crowding is negatively associated with niche entry.

Hypothesis 3B: Global crowding is positively associated with niche entry.

3.4 Niche status

We have mentioned that density has received criticism because the assumption that populations are homogeneous is erroneous. Here, we follow this train of thought, and argue that, even though community density is a good approximation to represent processes of legitimation at the community level (i.e., legitimation of the technological community in the wider environment), it is not a good measure to distinguish between the different levels of legitimation of technological forms within the community. So, what is needed is a measure for legitimation of our community members or technological forms relative to one another. This construct is labeled status, and can be defined as a focal member's perceived quality in relation to the perceived quality of other population members (Podolny, 1993; Shrum & Wuthnow, 1988). So, status is an instance of endogenous population structuring which results from the interactions of members in a population.

Akin to the importance of legitimation in the formative (or uncertain) stages of population development, status is 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 resource controllers thus need to rely on social considerations (i.e., status) to guide their decisions (Merton, 1968; Shrum et al., 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 depend on status, status becomes important in guiding the flow of resources in technological developments. As other organizations build upon the focal organization's technology, a certain legitimacy or status is conferred to that focal organization's technology (Podolny et al., 1995). Here, akin to the explanation at the organizational level, we argue that, in building upon a focal technological form, a certain legitimacy or status is transferred to the focal form as it provides a signal to community stakeholders that the focal technological form is worthy of attention and resources (see figure 5).

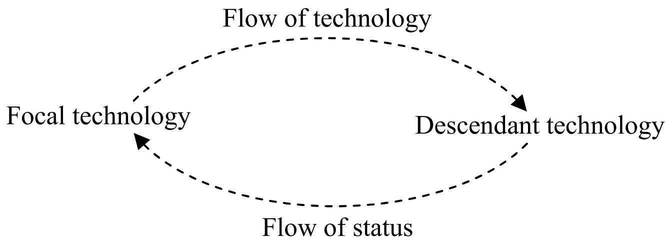

Figure 5 Technology and Status Flow in Technological Development

Hence, we argue that, in times of uncertainty, high-status niches offer an anchor for technological investment, attracting niche 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, as the developments within biotechnology in our period of investigation can be characterized by high levels of average uncertainty (Podolny et al., 1996), we expect status to have a positive effect on niche entry.

Hypothesis 4A (niche status): Status is positively associated with niche entry.

When alter organization builds upon the technology of a focal organization, it not only transfers a certain amount of status or legitimacy to the focal organization but also implies that the technology of alter and focal are similar, thus increasing the potential for competition between the organizations. Anticipating this, Podolny, Stuart, and Hannan (1996) argue that the effect of status is positive in uncrowded niches and that this positive effect decreases with crowding. According to the authors, direct ties have potentially the highest competitive impact in crowded regions of the technological space, as it results in a clique like structure, or structurally equivalent organizations (Burt, 1992). Even though this reasoning can also be applied when considering technological forms, we again have to make a distinction between the different levels of crowding (i.e., global and local) as we only expect local crowding to result in increased competition. We thus formulate our final hypotheses as follows.

Hypothesis 4B (interaction status and local crowding): At high levels of local crowding, status is negatively associated with niche entry

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 et al., 2004; Podolny et al., 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 et al., 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 technology in the broader technological environment.

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, and 9 in class 800) which are listed in table 1. As argued, we define our technological forms or niches at this level of analysis.

4.1 Measures

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

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

Community 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 our dependent variable, hereby also including focal niche density. To avoid double counting, we have subtracted focal niche density from community density in the measure labeled other density.

Table 1 Biotechnologies (Technological Niches)

Molecular and microbiology	
1	Differentiated tissue or organ other than blood, per se, or differentiated tissue or organ maintaining
2	Maintaining blood or sperm in a physiologically active state or compositions thereof or therefor or methods of in vitro blood cell separation or treatment
3	Condition responsive control process
4	Measuring or testing process involving enzymes or micro-organisms
5	Micro-organism, tissue cell culture or enzyme using process to synthesize a desired chemical compound or composition
6	Process of mutation, cell fusion, or genetic modification
7	Treatment of micro-organisms or enzymes with electrical or wave energy (e.g., magnetism, sonic waves, etc.)
8	Carrier-bound or immobilized enzyme or microbial cell
9	Enzyme (e.g., ligases (6.), etc.), proenzyme
10	Virus or bacteriophage, except for viral vector or bacteriophage vector
11	Animal cell, per se (e.g., cell lines, etc.)
12	Plant cell or cell line, per se (e.g., transgenic, mutant, etc.)
13	Spore forming or isolating process
14	Micro-organism, per se (e.g., protozoa, etc.)
15	Vector, per se (e.g., plasmid, hybrid plasmid, cosmid, viral vector, bacteriophage vector, etc.) bacteriophage vector, etc.)
16	Process of utilizing an enzyme or micro-organism to destroy hazardous or toxic waste, liberate, separate, or purify a preexisting compound or composition therefore
17	Apparatus
18	Miscellaneous (e.g., subcellular parts of micro-organisms, etc.)
19	Method of using a transgenic nonhuman animal in an in vivo test method (e.g., drug efficacy tests, etc.)
20	Method of using a transgenic nonhuman animal to manufacture a protein which is then to be isolated or extracted
21	Nonhuman animal
22	Method of making a transgenic nonhuman animal
23	Method of using a plant or plant part in a breeding process which includes a step of sexual hybridization
24	Method of chemically, radiologically, or spontaneously mutating a plant or plant part without inserting foreign genetic material therein
25	Method of producing a plant or plant part using somatic cell fusion (e.g., protoplast fusion, etc.)
26	Method of introducing a polynucleotide molecule into or rearrangement of genetic material within a plant or plant part
27	Plant, seedling, plant seed, or plant part, per se

Niche crowding refers to the extent to which our focal niches (i.e., biotechnologies' component technologies) overlap with other niches. First of all, to provide for our baseline model in testing our hypotheses regarding the distinction between local and global crowding, we first calculate the aggregate measure of crowding (i.e., <u>total crowding</u>). For this measure, we use the following formula:

$$NO_i = \sum_{j=1, j\neq i}^{j=J} \sum_{k=1, k\neq i, k\neq j}^{k=K} \frac{Min(A_{ik}, A_{jk})}{A_{ik}}, \qquad (1)$$

where NO_i refers to the niche overlap of focal niche i, A_{ik} refers to the number of antecedents of inventions niche i that come from niche k, A_{jk} refers to the number of antecedents of inventions niche j that come from niche k, and both J and K refer to the set of all niches, so both focal and non-focal niches.

As argued, we propose a distinction local and global crowding to disentangle the competitive and spillover effects. In our measure of <u>local crowding</u>, we calculate the overlap of our focal niche using (1). However, in this case, both J and K refer to the set of focal niches only. In our measure of <u>global crowding</u>, we measure the overlap of our focal niches with all other technological niches. To calculate this measure, we again use (1) but now, J refers to the set of all non-focal niches, whilst K refers to the set of all niches (so both focal and non-focal).

Focal <u>niche status</u> is measured on the basis of patent citations. Patent citations reveal community-wide perceptions of the relative importance of patented technologies (Trajtenberg, 1990), and can therefore be used to measure the status of the niche. Niche status is measured by the number of citations received by the niche in the previous twelve months. In line with Podolny and Stuart (Podolny et al., 1995), we use a ratio for niche status to correct for the expanding risk set of patents in our niches. However, we calculate status for a population of related invention (i.e., our technological niches), rather than for the organizations populating the niche. This implies

$$ST_{it} = \frac{\sum_{j=1}^{J} CR_{ijt}}{\sum_{k=1}^{k=K} CR_{kt}}, \qquad (2)$$

where CR_{ijt} is the number of citations received by invention j in niche i at time t, and CR_{kt} is the number of citations received by invention k from all drugs and medical technologies. This is represented by technology category 3 of Hall, Jaffe, and Trajtenberg's (2001b) classification, which is based on the USPTO-classification system and includes biotechnology. The reason for doing so is that this limits our status measure to the domain that we believe to be most relevant from biotechnology's perspective. Therefore, we believe we have a fair proxy for processes of legitimation. Furthermore, this significantly reduces the correlation between niche status, on the one hand, and niche density and organizational density, on the other hand, reducing potential problems of multicollinearity. Note that self-citations are excluded, as a self-citation does not adequately reflect the public deference process that this variable is supposed to represent (Podolny et al., 1996). Regarding the interactions between status and our crowding measures, we have mean-deviated the variables included in the interaction to reduce the correlation between the main effects and interaction terms.

Focal <u>Niche diversity</u> is measured via the distribution of patents across the technological components contained in the focal niche over the previous twelve months. The technological components of the niche are represented by the USPC sub-classes that are associated with the focal niche. To measure niche diversity, we will use Shannon's (1948) diversity measure, which is specified as:

$$D_{it} = \sum_{j=1}^{j=J} P_{ijt} \ln(1/P_{ijt}), \qquad (3)$$

where D_{it} refers to the diversity of niche i at time t, and P_{ijt} is the share of patents in category j at time t in niche i, and J refers to the number of categories (i.e., subclasses in our case).

Our first control variable is <u>organizational density</u>, which is a count of the number of organizations in the niche (in thousands). Legitimation of technology is to a large extent determined by the number of organizations that adopt the technology (Duysters, 1995). However, as competition speeds up the rate of scientific discovery, increasing the number of organizations, this means that the chances for discovery decrease. In such circumstances, the best defense is to retaliate in kind, and control another piece of technology as well (Stuart, 1999). This leads to ineffective strategies of technological development, depressing the technology's growth. We therefore expect to find an inverted U-shaped effect of organizational density on niche growth.

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

Table 2 Definition of Variables

Variable	Type *	Description
Niche entry	DV	Number of patents entering the focal niche in the current month
Previous entry	C	Number of patents entering the focal niche in the previous month
Organizational density	C	Number of organizations active in the focal niche in the previous 12 months
Community density	IV	Number of patents in the community in the previous month
Other density	IV	Number of patents in the community in the previous month excluding the focal niche
Niche density	IV	Number of patents in the focal niche in the previous month
Niche diversity	IV	Shannon's diversity index of the distribution of patents over subclasses in the focal niche in the previous 12 months
Niche status	IV	Ratio of patent citations received by focal niche in the previous 12 months
Total crowding	IV	Niche overlap between focal niche and all other niches in the previous 12 months
Local crowding	IV	Niche overlap between focal niche and focal niches in the previous 12 months
Global crowding	IV	Niche overlap between focal niche and non-focal niches in the previous 12 months

* DV = dependent variable; C = control variable; IV = independent variable

In table 2, we provide an overview of the variables and their definition. Descriptive statistics of the variables are provided in table 3. Next to the mean and the standard deviation, as usual, we also include the 25^{th}, 50^{th}, and 75^{th} percentile as these statistics better describe the distribution of skewed variables. The correlation matrix is provided in table 4.

Table 3 Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	25th %	50th %	75th %
Niche 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
Community density	17.228	11.447	4.983	44.962	8.102	13.051	23.524
Other density	16.554	11.166	2.879	44.954	7.701	12.551	22.606
Niche density	0.669	1.628	0.001	15.139	0.022	0.085	0.571
Niche diversity	1.827	1.496	0.000	4.706	0.000	1.931	3.172
Niche status	0.005	0.009	0.000	0.060	0.000	0.001	0.006
Total crowding	0.077	0.059	0.000	0.306	0.029	0.079	0.113
Local crowding	0.049	0.043	0.000	0.218	0.009	0.044	0.078
Global crowding	0.072	0.056	0.000	0.292	0.023	0.074	0.106

Table 4 Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11
1	Niche entry	1.00										
2	Previous entry	0.93	1.00									
3	Organizational density	0.94	0.94	1.00								
4	Community density	0.24	0.24	0.28	1.00							
5	Other density	0.11	0.12	0.15	0.99	1.00						
6	Niche density	0.88	0.88	0.95	0.24	0.10	1.00					
7	Niche diversity	0.38	0.38	0.46	0.00	-0.08	0.48	1.00				
8	Niche status	0.74	0.74	0.81	0.00	-0.13	0.83	0.61	1.00			
9	Total crowding	-0.11	-0.11	-0.10	0.23	0.25	-0.12	0.10	-0.11	1.00		
10	Local crowding	-0.08	-0.08	-0.06	0.49	0.51	-0.10	0.00	-0.16	0.69	1.00	
11	Global crowding	-0.11	-0.11	-0.10	0.21	0.23	-0.12	0.10	-0.11	1.00	0.65	1.00

The high correlations among the density variables (organizational density and niche density), niche status, and previous entries, imply high multicollinearity, which means we have to proceed with caution.[1]

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 niches 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 et al., 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 niches 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, forming the Poisson regression model is of the following general form (Hannan et al., 1995):

$$\Pr\{Y_{it} = y_{it}\} = \frac{e^{-\lambda_{it}} \lambda_{it}^{y_{it}}}{y_{it}!}, \tag{4}$$

where $\lambda_i(t)$ is the deterministic function of the covariates.

However, using the Poisson distribution for modeling economic events involves quite strong and empirically questionably 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 et al., 2000). One way to deal with overdispersion is to allow for inter-niche heterogeneity by permitting niche 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 et al., 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 accommodats for the existence of serial correlation (i.e., unobserved heterogeneity) between the repeated observations of the observed entities (in our case, technological niches) (Hausman et al., 1984). A negative binomial panel

[1] 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 <u>and</u> 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.

model can be represented by the following equation (Benner and Tushman, 2002):

$$\log \lambda_{it} = \beta X_{it} + \gamma \varepsilon_i + \mu_i, \tag{5}$$

where X_{it} is a vector of characteristics of niche i at time t; and γ is a correction for overdispersion (i.e., when the variance is greater than the mean); μ_i is a time invariant effect for each entity or niche 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-niche estimates. In the random effects version, the entity or niche specific term is drawn from a specified distribution (Cameron et al., 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 uncorrelated with the regressors. To determine whether or not this correlation is significant, we can use Hausman's (1978) specification test. 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:

$$H = (\beta_c - \beta_e)'(V_c - V_e)^{-1}(\beta_c - \beta_e), \tag{6}$$

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 et al., 1995): (a) do not control for quality differences at all; (b) treat quality differences as unobserved heterogeneity, and include previous occurrences of the dependent variable; and (c) rely on quality measures that are established in the relevant literature. In this paper, 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 et al., 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 the density measures (i.e., niche density, community density, and organizational density) and niche status forces us to proceed with caution to ensure that our findings are not the result of multicolinearity. We therefore estimate a number of models with alternative specifications of density dependence. Stability of our estimates over these alternative models 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 also known as the Generalized-Yule (GY) model and be specified as follows.

$$\lambda_{it} \propto N_{it}^{\alpha} \exp(\beta N_{it}^2), \tag{7}$$

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

An alternative model that is also used a lot in ecological studies is the Log-Quadratic (LQ) specification which has the following functional form.

$$\lambda_{it} \propto \exp(\alpha N_{it} + \beta N_{it}^2), \tag{8}$$

where again, λ_{it} is the rate of entry in niche i at time t, and n_{it} refers to the density of niche 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 distinction is mainly in how processes of legitimation are represented by the different models. The GY-model allows for a decreasing positive effect only, while the LQ-specification also allows for an increasing positive effect. Processes of legitimation are mainly important at the formative stage of a population. According to density dependence theory, each additional entry contributes less to the legitimation of the population that the previous entrant. Therefore, Hannan and Carroll (1992) have a preference for the GY-model over the

LQ-model as it connects better to the original theory. However, when GY-models do not converge or when LQ-models results in a much better fit, LQ-models can also be used.

Here, we follow the same strategy and estimate both the GY- and LQ- models and select the model that provides for the better fit. If both specifications result in consistent findings, we can also be more confident that our findings are not the result of multicolinearity. We first investigate what the best representation is of organizational density as this is an important control in our models by estimating both the GY and LQ model for organizational density. After this, we look for the best representation of niche density by again estimating both specifications.

Regarding our multilevel specification, besides estimating the GY and the LQ specification, we also need to consider whether processes of legitimation and competition operate on community or niche level, or both. As we expect processes of legitimation to operate more broadly than processes of competition, we assume that at the community level processes of legitimation are always present, while at the niche level processes of competition are always present.

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, commercial activity within biotechnology only took of after 1980 (Sorensen et al., 2000). Furthermore, we have data on a cross-section of different technologies within biotechnology, implying that several new and emerging technologies are represented. However, we should still treat our findings with some caution (Carroll et al., 2000) [2].

5 Results

Tables 6, 8, and 9 present estimates for the random-effects negative binomial dispersion model of patent counts. The models were estimated with the XTNBREG command in Stata, version 8.0. As previously noted, to ensure that our findings are not the result of multicolinearity, we proceed with caution and therefore build up our final model through stepwise regression. This means that we build our models incrementally. 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-likelihood to a chi-squared 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. Furthermore, we also estimate both the GY and the LQ specification of our density measures. The alternative models with which we start our analyses are displayed in table 5.

Table 5 Alternative Specification for (Organizational and niche) Density Dependence

NR	Type	Specification
1	LQ	$\lambda_{it} \propto \exp(\alpha O_{it} + \beta O_{it}^2)$
2	GY	$\lambda_{it} \propto O_{it}^{\alpha} \exp(\beta O_{it}^2)$
3	LQ	$\lambda_{it} \propto \exp(\alpha N_{it} + \beta N_{it}^2)$
4	GY	$\lambda_{it} \propto N_{it}^{\alpha} \exp(\beta N_{it}^2),$

Legend Type=Specification of density dependence; NR=Model number; O=Organizational density; N=Niche density

As can be seen in table 5, we start with determining the appropriate specification of organizational density using the estimates from models 1 and 2. Model 1 estimates the LQ specification and model 2 the GY specification. Comparing the Log Likelihood of models 1 and 2 in table 6 below, it becomes clear that the GY model (model 2) provides a better fit for organizational density. Note that the

[2] 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 legitimation processes.

parameter estimates are not standardized and should be interpreted as multiplier effects on the rate of niche entry, which means that the coefficient values should be exponentiated before interpretation.

Table 6 Estimates Organizational and Niche Density Dependence

	Model 1	Model 2	Model 3	Model 4
	Niche entry	Niche entry	Niche entry	Niche entry
Previous entry/1000	8.191134***	6.847843***	8.111957***	6.933611***
	[1.764136]	[1.039707]	[1.192404]	[1.010922]
(Previous entry/1000)^2	-22.175336***	-16.342949***	-21.457065***	-17.418012***
	[8.173322]	[4.665007]	[5.265225]	[4.606995]
Organizational density/1000	4.581005***			
	[0.499308]			
LN(Organizational density)		0.773474***	0.775167***	0.532006***
		[0.021480]	[0.021560]	[0.031853]
(Organizational density/1000)^2	-6.179981***	-0.799332***	-0.459729*	-0.868592***
	[0.559113]	[0.155791]	[0.270777]	[0.240307]
Niche density/1000			-0.048396**	
			[0.021735]	
LN(Niche density)				0.269036***
				[0.026329]
(Niche density/1000)^2			1.763561*	0.233981
			[1.030875]	[0.456173]
Constant	1.774415***	-0.882760***	-0.796875***	-1.788417***
	[0.073864]	[0.103379]	[0.111874]	[0.138411]
Observations	8021	8021	8021	8021
Number of niches	27	27	27	27
Degrees of freedom	31	31	33	33
r	1.83773	8.141454	7.788489	9.881957
s	0.768981	3.969791	3.697962	5.046364
Log likelihood	-12352.80	-11630.00	-11627.30	-11577.90

Closer investigation of the effect of organizational density on niche entry in models 1 reveals a non-monotonic inverted U-shaped relationship. This implies that organizational density both has a positive (i.e., legitimation processes) and a negative (i.e., competitive processes) effect on niche entry. However, according to the better fitting model 2, only processes of legitimation are present as we find a decreasing positive association between organizational density and niche entry. Subsequent models also support the findings of model 2. So, we continue with this model as the baseline for our subsequent analyses. That is, in our further models, we use the GY specification of organizational density as our baseline model.

Next, we determine the appropriate specification for niche density (see 5 above). Model 3 represents the GY specification of niche density and model 4 the LQ specification. Comparing the Log-likelihood values of models 3 and 4 in table 6 above clearly indicates that the GY specification is also superior in representing niche density dependence. After all, the Log-likelihood of model 4 is approximately 50 points higher (less negative) than model 3's Log-likelihood value. What's interesting to note is that, in contrast to hypothesis 1, the squared term of niche density is positive in both specifications (i.e., models 3 and 4).[3] So, it appears that competitive processes are not tied to niche density in our dataset. We will come back to this in the discussion part where we discuss our findings in greater detail.

We now continue and investigate multilevel density dependence. As argued, several specifications are possible in this respect. These specifications represent alternative models that specify processes of legitimation and competition at different levels of analysis. As noted before, consistent with the theory and to reduce the number of alternatives, we assume processes of legitimation to be present always at the community level and processes of competition to be present always at the niche level.

[3] Even though the linear term of niche density is negative and highly significant in model 3, this does not imply a competitive effect because the positive effect dominates the relationship over the entire range of observation.

Table 7 Alternative Specifications for Multilevel Density Dependence

NR	Type	Specification	Community level	Niche level
5	LQ	$\lambda_{it} \propto \exp(\alpha C_t + \beta N_{it}^2)$	Legitimation	Competition
6	LQ	$\lambda_{it} \propto N_{it}^{\alpha} \exp(\beta P_t + \delta N_{it}^2)$	Legitimation	Legitimation & competition
7	LQ	$\lambda_{it} \propto \exp(\alpha C_t + \beta P_t^2 + \delta N_{it}^2)$	Legitimation & competition	Competition
8	LQ	$\lambda_{it} \propto N_{it}^{\alpha} \exp(\beta P_t + \delta P_t^2 + \pi N_{it}^2)$	Legitimation & competition	Legitimation & competition
9	GY	$\lambda_i(t) \propto C_t^{\alpha} \exp(\beta N_{it}^2)$	Legitimation	Competition
10	GY	$\lambda_{it} \propto P_t^{\alpha} N_{it}^{\beta} \exp(\delta N_{it}^2)$	Legitimation	Legitimation & competition
11	GY	$\lambda_{it} \propto C_t^{\alpha} \exp(\delta P_t^2 + \pi N_{it}^2)$	Legitimation & competition	Competition
12	GY	$\lambda_{it} \propto P_t^{\alpha} N_{it}^{\beta} \exp(\delta P_t^2 + \pi N_{it}^2)$	Legitimation & competition	Legitimation & competition

Legend L=Legitimation; C=Competition; Type=Specification of community density; NR=Model number; N=Niche density; C=Community density; P=Other density.

The alternative models are displayed in table 7. Here, the baseline model that we will use specifies both organizational and niche density as a GY process. As such, in table 7, we only list the specifications that comply with the above assumptions. As can be seen in this table, a distinction is made between community density (represented by C_t in table 7) and other density (represented by P_t in table 7). As mentioned previously, the reason for doing this is to avoid double counting. So, when the linear term of niche density is included in the analysis, we exclude it from community density, hence, our measure of other density. The same rule applied for the quadratic and logged term.

As can be seen in tables 8 and 9, multilevel processes are clearly present in our setting. On the one hand, all models allow for a positive effect of density at the community level, which indicates that processes of legitimation at certainty present. On the other hand, we do not find a consistent negative effect of community density (or other density), which means that competitive processes are not well represented (or even absent altogether) at this level. Model 8, which represents density at the community level as a Log-quadratic specification, provides the best fit (Log-likelihood of 11558.50) and has a significant negative coefficient for the quadratic term. However, this does not imply competitive processes to be present at the community level. After all, the point of inflexion lies well above the maximum value of this measure (i.e., a decreasing positive effect).

Table 8 Estimates Multilevel Density Dependence

	Model 5	Model 6	Model 7	Model 8
	Niche entry	Niche entry	Niche entry	Niche entry
Previous entry/1000	6.601079***	7.837435***	7.317674***	8.090414***
	[1.044211]	[1.036933]	[1.078487]	[1.046437]
(Previous entry/1000)^2	-16.993627***	-21.861164***	-19.337504***	-23.039895***
	[4.762809]	[4.764799]	[4.871491]	[4.811835]
LN(Organizational density)	0.771346***	0.533355***	0.763613***	0.523307***
	[0.021518]	[0.031833]	[0.021662]	[0.032208]
(Organizational density/1000)^2	-0.509917**	-0.470500*	-0.687878***	-0.151419
	[0.247595]	[0.252142]	[0.257043]	[0.298707]
Community density/1000	0.048762***		0.009292	
	[0.008907]		[0.016200]	
Other density/1000		0.047723***		0.083802***
		[0.008157]		[0.019887]
(Other density/1000)^2			0.000664***	-0.000605**
			[0.000227]	[0.000303]
LN(Niche density)		0.270004***		0.291722***
		[0.026432]		[0.028578]

	Model 5	Model 6	Model 7	Model 8
(Niche density/1000)^2	-0.600191	1.925057***	2.545166**	0.620935
	[0.466339]	[0.538668]	[1.170111]	[0.848887]
Constant	-2.957192***	-3.776241***	-2.376333***	-4.331004***
	[0.396399]	[0.366767]	[0.444278]	[0.461159]
Observations	8021	8021	8021	8021
Number of niches	27	27	27	27
Degrees of freedom	33	34	34	35
r	8.141324	9.652923	7.789093	9.864177
s	3.890242	4.751092	3.6322	4.889322
Log likelihood	-11614.80	-11560.50	-11610.50	-11558.50

Table 9 Estimates Multilevel Density Dependence

	Model 9	Model 10	Model 11	Model 12
	Niche entry	Niche entry	Niche entry	Niche entry
Previous entry/1000	6.862298***	6.569916***	7.550031***	6.985767***
	[1.046302]	[1.019905]	[1.055891]	[1.032553]
(Previous entry/1000)^2	-16.811895***	-16.562529***	-19.999372***	-18.400500***
	[4.761924]	[4.635401]	[4.832029]	[4.705710]
LN(Organizational density)	0.775383***	0.523968***	0.755416***	0.534309***
	[0.022384]	[0.031805]	[0.022614]	[0.031979]
(Organizational density/1000)^2	-0.629035**	-0.422664	-0.839754***	-0.561342**
	[0.270347]	[0.263912]	[0.271763]	[0.267240]
(Other density/1000)^2			0.000803***	0.000450***
			[0.000128]	[0.000130]
LN(Community)	0.071065	0.609030***	-0.14955	0.444143***
	[0.143277]	[0.148728]	[0.144266]	[0.155150]
LN(Niche density)		0.308028***		0.282408***
		[0.027969]		[0.029050]
(Niche density/1000)^2	-0.333499	-0.143262	3.309753***	1.890915**
	[0.479107]	[0.466764]	[0.744807]	[0.746186]
Constant	-1.633213	-8.480207***	-0.600558	-7.377789***
	[1.545703]	[1.637667]	[1.523454]	[1.660597]
Observations	8021	8021	8021	8021
Number of niches	27	27	27	27
Degrees of freedom	33	34	34	35
r	8.127113	10.315085	7.68325	9.934697
s	3.956793	5.305456	3.566813	4.972907
Log likelihood	-11629.70	-11569.40	-11610.10	-11563.40

Model 13 estimates our baseline model (i.e., model 8) and adds our non-density variables (i.e, niche diversity, niche crowding, and niche status). Comparing the Log-likelihood value of model 8 (-11558.50) with that of model 13 (-11547.30) shows that model 13 significantly improves model fit (Chi2 of 22.4 with 3 degrees of freedom). However, adding the interaction term of status and crowding in model 14 does not significantly improve model fit (Chi2 of 2.2 with 1 degree of freedom).

Model 15 makes a distinction between local and global crowding and significantly improves model fit. Moreover, adding the interaction terms of, on the one hand, local crowding and status, and on the other hand global crowding and status also significantly improves model fit. As such, we use model 16 to discuss the findings of our hypotheses. Moreover, we have also estimated Model 16 using a fixed-effects specification, and conducted Hausman's specification test to investigate the extent to which the random-effects specifications are indeed appropriate. This test compares the coefficient estimates of the consistent (fixed-effects model) and the efficient (random-effects model) estimation. When these estimates do not deviate too much, the efficient estimation can be used as it provides roughly the same coefficient estimates as the consistent estimation. This test provides strong evidence in favor of a random-effects specification, showing no systematic difference between the coefficients of the different models (Chi2(38) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 14.05, Prob>chi2 = 0.9999). This supports our conjecture that we have no problems of unobserved heterogeneity. As noted, model 16 provides the best fit and we will use the estimates from this model in the discussion of our results, unless otherwise stated.

Table 10 Estimates Full Model

	Model 13	Model 14	Model 15	Model 16
	Niche entry	Niche entry	Niche entry	Niche entry
Previous entry/1000	7.847061***	7.804602***	7.393650***	8.283784***
	[1.086152]	[1.086292]	[1.096823]	[1.140871]
(Previous entry/1000)^2	-22.707822***	-22.432323***	-20.967280***	-24.319170***
	[5.011557]	[5.011997]	[5.038526]	[5.205391]
LN(Organizational density)	0.541322***	0.531949***	0.531448***	0.501731***
	[0.033144]	[0.033744]	[0.033182]	[0.034279]
Organizational density^2	0.102247	-0.051133	0.012657	-0.228078
	[0.331857]	[0.347145]	[0.333296]	[0.350239]
Other density/1000	0.083566***	0.085951***	0.085367***	0.103387***
	[0.020406]	[0.020487]	[0.020381]	[0.020954]
(Other density/1000)^2	-0.000640**	-0.000690**	-0.000628**	-0.001035***
	[0.000313]	[0.000315]	[0.000312]	[0.000331]
LN(Niche density)	0.352265***	0.363324***	0.347894***	0.371784***
	[0.031881]	[0.032772]	[0.031843]	[0.033023]
(Niche density/1000)^2	1.219272	1.047207	1.223824	-0.075316
	[0.908361]	[0.915874]	[0.907072]	[0.968893]
Niche diversity	-0.088123**	-0.086583**	-0.085807**	-0.093469**
	[0.041496]	[0.041578]	[0.041318]	[0.041957]
Niche status	-13.045374***	-16.980502***	-12.095042***	-18.926813***
	[3.302872]	[4.247415]	[3.313791]	[4.321755]
Niche crowding/1000	-0.374788	-0.713908		
	[0.371635]	[0.436851]		
Status * crowding/1000		-0.107604		
		[0.072635]		
Local crowding/100			-1.900202***	-2.573189***
			[0.675109]	[0.698298]
Global crowding/1000			0.30515	0.036661
			[0.444349]	[0.492422]
Status * Local crowding/100				-264.365964***
				[75.855652]
Status * Global crowding/1000				-41.646443
				[76.498099]
Constant	-4.367053***	-4.377041***	-4.314485***	-4.283518***
	[0.469564]	[0.469864]	[0.469506]	[0.470958]
Observations	8021	8021	8021	8021
Number of niches	27	27	27	27
Degrees of freedom	38	39	39	41
r	8.465956	8.438579	8.386421	7.98045
s	3.981347	3.953155	3.906994	3.616103
Log likelihood	-11547.30	-11546.20	-11543.40	-11536.30

Hypothesis 1A argues that niche density has an inverted U-shaped effect on niche entry. This hypothesis is only partly supported by our estimates as we only find a significant positive association between niche density and niche entry. Even though some models (also our final model 16) do find a negative association, this is a non-significant one. Furthermore, closer investigation of the estimates of model 16 reveals that it only decreases the positive effect. Hence, it is obvious that only the legitimation part of this hypothesis is supported. Increasing density from its first quartile to its median value increases niche entry with 64.19%. Further increasing niche density from its median value to its third quartile increases the rate of niche entry with as much as 97.84%.

According to hypothesis 1B, density at the community level is positively tied to the process of niche entry due to the existence of legitimation processes. To avoid double counting, model 16 uses other density (=community density – density). This hypothesis is fully supported by our findings. All multilevel models find a significant positive coefficient for community density (or other 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 measures normal range and even above its maximum value (-0.10/(2*0.001)=50). This clearly points to the existence of processes of legitimation at the community level. On the one hand, subtracting a standard deviation from the mean value of other density reduces niche entry with 59.38%. On the other hand, adding a standard deviation to its mean value increases the rate of entry with 90.17%. Closer investigation of the functional relationship reveals a decreasing positive effect of other density on the rate of niche entry.

Hypothesis 2 posits that niche diversity has a positive association with the rate of niche entry. This hypothesis is fully rejected by our estimates. Instead of a positive effect, we find a significant negative effect in all models that include diversity as an independent variable (i.e., models 13 to 16). In model 16, increasing the value of niche diversity with one standard deviation decreases the rate of niche entry with 13.05%.

We do find full support for hypothesis 3A. According to this hypothesis, local crowding has a negative effect on niche entry due to competitive processes. As can be seen in models 13 to 16 in table 10 above, crowding does not have a significant effect on niche entry until separated into its local and global component. The coefficient for local crowding is highly significant and negative. Increasing local crowding with one standard deviation decreases the rate of niche entry with 10.41%.

In contrast to hypothesis 3A, we do not find full support for hypothesis 3B. This hypothesis states that global crowding is positively associated with niche 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 being significant.

Our analyses also do not substantiate Hypothesis 4A, which claims that the main effect of niche status is positively associated with niche entry due to the inherent uncertainty of development in biotechnology. Instead of the expected positive coefficient, we find a highly significant negative coefficient. On the one hand, increasing the value of niche status from its median value to its third quartile decreases the rate of entry with 8.19%. On the other hand, decreasing the value of status from its median value to its first quartile increases the rate of niche entry with 2.24%. So, even though the negative effect of status is rather small, this warrants further investigation and contemplation. We will return to this in discussing these findings in the next section of this chapter.

Finally, hypothesis 4B argues that the interaction of local crowding and niche status is negative due to dominance of competitive processes in locally crowded niches. This hypothesis is fully supported by our estimates as we find a highly significant negative coefficient for the (mean deviated) interaction term. Figure 6 below shows the effects of the interaction between these variables.

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 niche 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 paper. Finally, regarding previous entries, the coefficient for the linear term is positive and highly significant and 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 (0.17) lies well beyond this measures normal range, implying that previous entry increases subsequent entry at a decreasing rate.

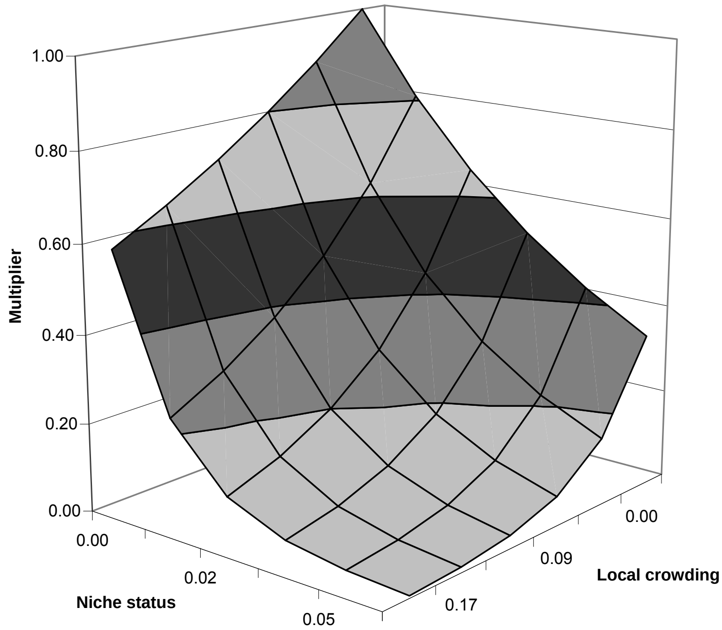

Figure 6 Interaction Niche Status and Local Crowding

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 is that a structural (or ecological) perspective has been relatively underdeveloped. This study has addressed this problem 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 niches. Many ecological variables significantly impact upon a focal niche's growth (see table 13 below). In all, we find full support for three 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 a technological form or a population related inventions. 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 six of these.

Table 13 Overview Hypotheses

Hypothesis		Expected	Found	Significance	Result
1a	Niche density	∩	↑	***	Partially
1b	Community density	↑	↑	***	Accept
2	Niche diversity	↑	↓	**	Reject
3a	Local crowding	↓	↓	***	Accept
3b	Global crowding	↑	↑		Not accept
4a	Niche status	↑	↓	***	Reject
4b	Status * Local crowding	↓	↓	***	Accept

* significant at 10%; ** significant at 5%; *** significant at 1%

First, our results clearly illustrate a positive association between niche density and niche entry. This provides strong evidence for density dependent processes, that is, that processes of legitimation are tied to density. However, we have to note here that the increasing positive effect of density on niche entry does not fully conform to processes of legitimation. After all, according to the theory, processes of legitimation have a decreasing positive effect of density on niche entry. So, the fact that we find an increasing positive effect is indicative of the existence of positive externalities as well. Therefore, the question becomes whether we are observing processes of legitimation at all, or just processes driven by positive externalities. The fact that we do not find competitive processes being tied to density further complicates this issue. However, this does not fully undermine our arguments about the applicability of the theory of density dependence to technological populations. After all, the existence of competitive processes is idiosyncratic to our domain of investigation, that is, biotechnology. The reason is that it is well-known that biotechnology is a relatively young technology, still in its formative or growth stage of development. In these stages, competitive processes play a relatively small role and are extremely difficult to detect as the relationship between density and niche entry is dominated by processes of legitimation. Hence, further research is needed whether competitive processes can also be tied to density and whether density dependent logic can be applied at all in technological populations. Here, investigation of more mature technological domains (i.e., semiconductors) is especially warranted as this not only allows the validation of the competitive part of density theory, it also allows a further comparison between relatively young and more mature technologies.

Second, instead of a positive effect we have found a significant negative effect of niche diversity on niche entry. Even though this leads to a rejection of our hypothesis, this does underscore the critical role of diversity in processes of technological change. This is not surprising, considering that diversity is the variability on which selection operates. Closer investigation of the relationship between diversity and niche entry leads us to believe that the negative association between diversity and niche entry is connected to the existence of different stages of technological growth. Basically, the density dependence argument already assumes different stages of population evolution. In the formative stage or population development, legitimation processes dominate. If a population is fully legitimized, legitimation is no longer an issue and competitive processes become more important. As argued, here, we do not yet observe the existence of competitive processes. So, in this formative stage of development, diversity seems to impede legitimation. This connects to the work of Bogeart, Boone, and Carroll (2007), who argue that heterogeneity hampers the legitimation process. It thus seems that diversity, like density, plays a twin role in the evolution of a population. 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). Furthermore, such a theory would not only have to consider niche entry, but also take into account the process of niche emergence, which is perceived by many as the creation of true novelty. This also relates to the form emergence literature in organizational ecology (Ruef, 2000).

Third, in contrast to our hypothesis, we have found a significant negative association between niche status and niche entry. So, apparently, niche status points to competitive processes due to technological similarity, instead of providing an anchor for investments as argued in our hypothesis. This finding also points to the existence of different stages of technological evolution. However, it does not conform to our expectations in of a formative stage of technological development. Hence, it appears that we have included in different stages of technological development in our analysis. After all, in the formative stage of development, status is expected to have a positive effect on niche entry due to the inherent uncertainty of this stage of development. This means that the negative effect of status indicates that our analysis is dominated by niches in a later stage of technological development, in which the positive effect of status has already evaporated. Hence, a closer investigation into the existence of different stages of technological development is certainly warranted, and might reveal that the effect of status on niche entry is conditional upon the stage of technological development. This connects nicely to the literature on technological change and development, which clearly distinguishes between the level of uncertainty in the early formative stage of technological development and the subsequent stage of growth or maturity. We will return to this issue in great detail in the next chapter.

Fourth, we demonstrated that because of processes of both competition and positive spillovers, it is necessary to make a distinction between local and global crowding. By not distinguishing between local and global crowding, we found a non-significant negative association between crowding and niche entry. So, it appears that competitive processes dominate the relationship between crowding and niche entry. However, because the coefficient is not significant, no conclusion can be drawn. So, by aggregating the individual components of crowding it appears that there is no positive effect of crowding, which explains why crowding has been commonly equated with competitive processes within organizational ecology. However, if we decompose crowding into its local and global components, a different picture emerges. On the one hand, the estimates from model 16 clearly illustrate a persistent negative effect of local crowding, implying that competitive processes dominate the relationship between local crowding and niche entry. Furthermore, the highly significant negative interaction term between status and local crowing makes the competitive effect of local crowding even more apparent. As mentioned, this connects nicely to the localized competition hypothesis and the observation that legitimation processes operate more than do competitive processes. On the other hand, global crowding has a positive, though not significant, positive effect on niche entry. Furthermore, the interaction between global crowding and status is negative and not significant. We do have to note that further decomposing global crowding into its component parts (and interacting these terms with status) demonstrates an even more intricate relationship between crowding and niche entry and warrants further investigation. However, such an investigation lies outside the scope of this paper and therefore has to be left for future research.

Fifth, an important limitation of our study is that we have abstracted from the role of the innovating organization. Our results clearly indicate that organizations play a major role in the process of technological niche growth. In future work, we hope to develop a multi-level model, where the evolution of organizations and that of technologies are considered simultaneously. This is a natural extension of the population perspective developed above, as it is well recognized that organizations and technologies co-evolve. Here, we would like to briefly reflect on two such extensions. First of all, we need a theory of 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 new forms of organizations. 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 et al., 1989). Moreover, at the level of an individual organization, we can relate the dynamics of technological niches to the characteristics of an organization’s technological search behavior. Organizations search as members of a population (Podolny et al., 1995), and by focusing on technology we basically investigate the search pattern of a technological community. By relating an individual organization’s technological search to the pattern of search at the population (or community) level, we can determine the extent to which the organization’s search behavior conforms to or conflicts with the population-level 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 and are more new to the world, as well as to March’s (1991) notions of exploration and exploitation.

Sixth and finally, another limitation is that our empirical setting is the domain of biotechnology. Studying this technological field has the advantage that patents form a reliable indicator of processes of technological growth (Orsenigo et al., 2001; Powell et al., 1996) enhancing the internal validity of our study. However, a study into a single domain generally puts limits to the generalizibility of the findings. Biotechnology reflects a highly science-based innovation pattern, with an important role of 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). Moreover, molecular biology differs from other technologies by forming a relatively stand-alone technology (Teece, 1986). The potential for recombination of stand-alone technology may be larger, implying that the creative process may be more volatile than for a systemic technology with a modular set-up (Fleming et al., 2001). 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.

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