DEPARTMENT OF MANAGEMENT

THE ECOLOGY OF TECHNOLOGY

AN EMPIRICAL STUDY OF US BIOTECHNOLOGY PATENTS FROM 1976 TO 2003

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An empirical study of US biotechnology patents from 1976 to 2003

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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 of related inventions. 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 or systemic 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.

1. *Introduction*

Although the Schumpeterian (1943) 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 and 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 contribute to an explanation of the nature of the growth pattern that is associated with endogenous technological change.

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. In organizational ecology, the focus is on the evolution of a population of organizations. Adopting a similar logic, we deal with the evolution of a population of inventions. More specifically, by conceiving of technology as a system, we aim to determine to what extent the pattern of technological growth can be attributed to the systemic or structural characteristics of technology. It is in this sense that our approach deals with endogenous growth of a technology. We coin this new approach the 'ecology of technology'.

In line with the work of Podolny and Stuart (1995), we argue that the notion of a technological niche offers a platform from which we can develop a deeper understanding and explanation of this process. We define technology as a system that can be viewed as a set of interdependent technological niches or components. In turn, these niches or components are defined as populations of related inventions. Our key aim is to develop a theory of why growth rates differ across technological components due to the structural characteristics of technology. As we will argue in greater detail below, this process of endogenous technological growth is determined by the 'ecological' characteristics of a technological component and the way in which this component is embedded in the technological system and environment. This makes the concept of a technological niche useful by pointing to the important role of the systemic or 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 systemic perspective towards technology is warranted, bringing in insights from organizational ecology. Second, these technological growth patterns are to a large extent determined by structural characteristics of technology. 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.[1] In doing so, we extend the notion of the technological niche by adding internal diversity as a key structural feature, and illustrate the importance of adding a measure of technological diversity in evolutionary and ecological models of technological growth. Moreover, we apply models from organizational ecology to a technological population.

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[1] Note that given our focus on patent data, we operationalize growth as entry (normally, growth is equated with net entry – i.e., entry minus exit), as patents do not exit. Hence, in the remainder, technological growth and entry are used interchangeably.

2. *Endogenous technological growth*

Schumpeter (1943) presented an evolutionary theory of the workings of the capitalist system, driven by forces of technological change. He conceived technological change (i.e., growth) as a process of recombination, where (existing) components are brought together in new ways (Schumpeter 1939). Since then, the conception of technological growth as a process of recombination has been widely adopted in the literature (Fleming 2001; Fleming and Sorenson 2001; Henderson and Clark 1990; Nelson and 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.

In the current paper, we develop a theory of why growth rates differ across technologies due to the structural characteristics internal to technology itself. We view technology as a system that cuts across organizational boundaries (Barnett, 1990). We thus abstract from the individual organization, and focus instead on the aggregate pattern of development of all organizations that are active in a certain technological system (i.e., biotechnology). Accordingly, we use Hawley's (1950) ecological framework to study technology in terms of its elemental systems or components. So, in analogy with Ruef (2000), we define a technological system as a bounded set of technological components with a related identity. In turn, a technological component is defined as a population of related technological inventions. In doing so, we develop a multi-level model of technological growth.

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. Within the social sciences, the niche has received widespread attention in numerous empirical studies (Baum and Singh 1994; Dobrev, Kim and Hannan 2001; Freeman and Hannan 1983; Lawless and Anderson 1996; Podolny and Stuart 1995; Podolny, Stuart and Hannan 1996), as well as theoretical work (Hannan, Pólos and Carroll 2007; Péli 1997; Péli and Nooteboom 1999; van Witteloostuijn and Boone 2006).

The technological niche was first developed by Podolny and Stuart (1995) to investigate the effects of crowding and status on the future importance of individual inventions. They defined the technological niche as the relational context of an invention that co-evolves with technological change. Podolny et al. (1996) subsequently applied the concept of the technological niche at the organizational level of analysis, to study the effects of crowding and status on organizational growth and survival. In the current study, we want to continue in this tradition, and build on this notion of the technological niche. However, instead of applying the niche to individual inventions or to an organization's portfolio of inventions, we define the niche at the level of a technological component and investigate the aggregate pattern of development by all organizations active within a certain technological system. That is, we define the technological niche as the relational context of a technological component (e.g., genetic engineering), embedded within a technological system (e.g., biotechnology).

Our key dependent variable is growth of the technological component as reflected in entry by new inventions, coined component growth. Below, we will subsequently discuss the dimensions of the niche central to our theory, focusing on both its internal (i.e., niche density and diversity) and external (i.e., crowding and status) features. Note that, given our application to component niches of biotechnology, we often refer to the short-cut component for component niche.

Component density

Ecologists have observed a characteristic pattern of evolution of diverse organizational populations: initially, after a slow kick-off, population size -- measured in terms of the number of organizations, or density -- increases rapidly, and then stabilizes or even declines in numbers (Carroll 1984; Carroll and Hannan 1989a; Carroll and Hannan 2000; Hannan and Freeman 1989). Intrigued by the universality of this typical S-curved pattern, organizational ecologists have sought to explain this phenomenon. They were able to do so by integrating elements from ecological and institutional theories, into what is known as density dependence theory (Carroll and Hannan 1989a). This theory posits that the two general forces of selection – i.e., social legitimation and diffuse competition – are linked to the density of organizational populations (Carroll and Hannan 2000). Basically, population density serves as a surrogate for the difficult-to-observe features of the material and social environment that affect organizational founding and mortality rates, particularly competition and legitimation (Hannan and Freeman 1989).

Legitimation refers to “the standing as a taken-for-granted element in a social structure” (Hannan et al. 2007: 78), and is especially important in the early stages of population development. The capacity of an organizational form to mobilize resources is to a large extent dependent on the extent to which (extremely skeptical) resource controllers take the form for granted (Aldrich and Fiol 1994; Carroll and Hannan

2000). Legitimation is tied to density because, according to Hannan and Freeman (1987: 918), “if institutionalization means that certain forms assume a taken-for-granted character, then simple prevalence of the form ought to legitimate it.” Legitimation processes thus produce a positive relationship between population density and founding rates.

Density also has an obvious link with diffuse competition, which is defined as common dependence on the same resource pool. If density increases linearly, the number of potential competitive links increases exponentially (Carroll and Hannan 2000). This implies that density increases diffuse competition at an increasing rate, as more organizations fight for limited resources, resulting in declining founding rates and increasing mortality rates (Hannan and Freeman 1987). The joint forces of legitimation (dominant at low density) and competition (dominant at high density) produce non-monotonic density-dependent processes of organizational entry (hill-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 (van Witteloostuijn 2003; van Witteloostuijn and de Jong 2010) and organizational rules (March, Schulz and Shou 2000; Schulz 1998). In a similar vein, we believe that density dependence logic can fruitfully be used in the study of evolutionary processes within technological populations (Pistorius and Utterback 1997). Technology displays characteristic patterns of growth, and the S-shaped growth or logistics curve is extensively documented for technology, too (Andersen 1999; Griliches 1957; Rogers 1962;

Young 1993). However, we have to keep in mind that, even though similarities between technologies and organizations provide a useful platform for exporting analytical concepts from one domain to the other, we have to be careful not to equate one sphere with the other (Pistorius and Utterback 1997). This implies that we should carefully consider the extent to which processes of competition and legitimation operate in technological populations.

It is widely acknowledged that technologies need to be legitimized (Aldrich and Fiol 1994; Anderson and Tushman 1990; Duysters 1995; Zucker 1989). According to DiMaggio and Powell (1983), organizations even adopt technology to enhance their own legitimacy. Hence, technologies are institutionalized, becoming a taken-for-granted means to accomplish organizational ends (Meyer and Rowan 1977). This process of legitimation is especially important in the formative stage of a technology 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 and Carroll 2007: 3). Here, we believe that the denser the component’s technology (i.e., the more technological inventions there are in the component’s niche), the better understood the technological component is, and the more it is taken-for-granted as the appropriate means to accomplish a certain goal (e.g., use rDNA technology to modify the genetic structure of living material). This process enhances the growth of this technological component. Analogous to the acceptance of a new organizational form by society, legitimacy of a new technological component increases with the number of technological inventions in the component’s niche. Hence, at low levels of component density, we expect that component density stimulates component entry.

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

> ***Hypothesis 1****: Component density is first positively and later negatively associated with component growth, implying a non-monotonic hill-shaped effect of component density on component growth.*

System density

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

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

One of the proposed extensions is to employ multi-level models, where processes of legitimation are allowed to operate more broadly than competitive processes (Hannan et al. 1995). Here, we follow this line of reasoning by arguing that the flow of material resources (i.e., plants, products, and people) is not only disrupted by political and physical barriers (Carroll and Hannan 2000), but also by technological boundaries. That is, we claim that technology also localizes competitive processes, whilst processes of legitimation operate on a broader technological scale. Hence, we expect density within the entire technological system to be tied to processes of legitimation (and not to competition). After all, a set of components comprise a system only when these components form an integrated whole – that is, when the whole is greater than the sum of its parts.

Hypothesis 2*: System density is positively associated with component growth.*

Component diversity

Because population segments respond differently to processes of competition and legitimation, it is important to consider whether a population is subdivided into segments. In the context of our current study, three motives come to mind for considering such diversity. First, according to Durkheim (1933), there is an inverse relationship between diversification (i.e., diversity) and competition. That is, if a population becomes more diverse, the level of competitive intensity within the population decreases. So, as the rate of entry is tied to the competitive intensity within a technological component, we expect component entry to increase with component diversity. Second, diversity mitigates lock-in and provides flexibility in uncertain environments (Stirling 2007). Because technological development within biotechnology is of a highly uncertain nature, flexibility is important by providing alternative directions for future development. In this sense, diversity is indicative of niche width, and increasing the diversity of the niche increases its potential applicability in the wider environment, implying that it is appealing to a greater variety of stakeholders, which positively affects the rate of component entry. Third, and finally, technological change is a process of recombination (Schumpeter 1939), so increasing the number of subcomponents (in a component) increases the opportunities for their (re)combination, yielding further opportunities for the creation of new inventions.

Hypothesis 3*: Component diversity is positively associated with component growth.*

Component status

Even though processes of legitimation at the system level affect all components within the system, it is highly unlikely that system-level legitimation will affect all components equally. Furthermore, component density is a proxy that cannot accurately describe the distribution of system-level legitimation among components. This means that we need another way to distinguish between the legitimation of individual components relative to the other components within the technological system. A well-known construct that measures legitimation at the individual member level is status, which is defined as a focal member's 'perceived' quality in relation to the 'perceived' quality of other population members (Podolny 1993; Shrum and Wuthnow 1988).

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

According to these studies, as the uncertain environment makes quality perceptions dependent on status, status becomes important in guiding the flow of resources in technological developments. As other organizations build upon the focal organization's technology, a certain legitimacy or status is conferred to that focal organization's technology (Podolny and Stuart 1995). Here, akin to the explanation at the organizational level, we argue that, when aggregate technological developments build upon a focal technological component, a certain legitimacy or status is transferred to the focal component as it provides a signal to the stakeholders of the technological system that the focal component is worthy of attention and resources. So, in times of uncertainty, high-status components offer an anchor for technological investment (i.e., resources), attracting component entry. Podolny et al. (1996: 669) refrain from hypothesizing about the main effect of status because, as they argue, “one cannot specify an average status effect independent of a meaningful assessment of the average crowding or uncertainty in a technological domain.” However, because technological developments within biotechnology can be characterized by high levels of average uncertainty (Pisano 2006; Podolny et al. 1996), we expect status to have a positive main effect on component entry.

> ***Hypothesis 4****: Component status is positively associated with component growth.*

Component crowding

In ecological studies, niche crowding is usually equated with competition, as it implies a similarity in resource requirements (Baum and Mezias 1992; Dobrev et al. 2001; Hannan and Freeman 1977; Hannan and Freeman 1989; Hannan et al. 2007; Podolny et al. 1996), and builds upon the notion that the potential for competition is directly proportional to the overlap of resource bases (Baum and Singh 1994). In view of our technological components, the resource base can be properly represented by the knowledge on which the inventions within the component build. Especially when markets are not (yet) existent, technological development is to a large extent dependent on the underlying knowledge base (Duysters 1995).

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

However, niche crowding can also contribute in a positive way to niche entry or growth, due to reputation and knowledge spillovers (Fleming and Sorenson 2004; Jaffe 1986; Levin 1988), economies of standardization through a sharing of infrastructure (Baum and Haveman 1997; Wade 1995), and vicarious learning (Delacroix and Rao 1994). This mutualistic relationship has been validated empirically in numerous studies (Boone, Wezel and van Witteloostuijn 2004; Fleming 2001; Jaffe 1986; Levin 1988; Pontikes 2007; Spence 1984; Stuart 1999). Here, we explore the extent to which these arguments can also be applied when investigating aggregate patterns of technological development.

First, technology can become a taken-for-granted means to accomplish an organizational objective, implying the existence of legitimation or reputation spillovers from (the use of) one technology to the (use of the) other. Furthermore, knowledge spillovers within technological development are well-documented. As the usage of technology increases, the documentation of technology also increases – for example, in patent documents, manuals, and books. As a result, the characteristics and behavior of often used technologies are better known.

Second, economies of standardization or infrastructure sharing relate to the costs of transportation, communication, and ease of supply (Baum and Haveman 1997), which are important in the case of technological development, too. Consider, for example, the use of active compounds (e.g., molecules and proteins) in biological tests. Reliance on compounds that are not readily available obviously hampers technological development. Moreover, according to Pistorius and Utterback (1997), an emerging technology can benefit from the infrastructure that was created to accommodate the mature technology. Third, and finally, vicarious learning is possible through adaptation and selection of ideas, structures, and technologies (Delacroix and Rao 1994), which by definition play an important role in technological development.

How can we accommodate for both a positive and negative effect of component crowding? According to organizational ecology logic, processes of competition are more localized than processes of legitimation. More local or more similar organizations are more likely to vie for the same pool of resources (Barnett 1997). In a similar vein, we argue that more local technological components compete for the same resources, such as venture capital, investments, and research budgets. The competitive processes are bound by technological systems. This means that we distinguish between two forms of crowding. On the one hand, local crowding refers to crowding of our focal components amongst themselves (i.e., crowding within our technological system). On the other hand, global crowding refers to crowding of our focal component by non-focal components (i.e., crowding of our focal components by components outside the technological system).

Hypothesis 5*: Local crowding is negatively associated with component entry.*

Hypothesis 6*: Global crowding is positively associated with component entry.*

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

Hypothesis 7a*: The interaction term of local crowding and component status is negatively associated with component growth.*

Hypothesis 7b*: The interaction term of global crowding and component status is not negatively associated with component growth.*

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 and Sorenson 2004; Podolny and Stuart 1995; Sorensen and Stuart 2000; Stuart 1998;

Stuart 2000). Especially within biotechnology, patents form a reliable indicator of technological developments (Orsenigo, Pammolli and Riccaboni 2001; Powell, Koput and 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 and Stuart 1995). Furthermore, because the US is a large and central market for biotechnology, it is standard practice of biotechnology companies from outside the US to patent in this country (Albert et al. 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; Fleming and Sorenson 2004; Hall, Jaffe and Trajtenberg 2001; Jaffe, Trajtenberg and Fogarty 2000; Lanjouw and Schankerman 2004; Trajtenberg 1990). We therefore use these citations to delineate technological lineage and the embeddedness of a focal technological component 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. Hence, 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). As argued, we define our technological niches (i.e., components) at this level of analysis.

Measures

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

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

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

$$(1) \qquad CO_{it} = \sum_{j=1, j\neq i}^{j=J} \sum_{k=1, k\neq i, k\neq j}^{k=K} \frac{Min(A_{ikt}, A_{jkt})}{A_{ikt}},$$

where CO_{it} refers to the overlap experienced by focal component *i* at time *t*, A_{ikt} to the number of antecedents of component *i*'s inventions that belong to component *k* at time *t*, A_{jkt} to the number of antecedents of component *j*'s inventions that belong to component *k* at time *t*, both *J* and *K* refer to the set of all components, so both focal and non-focal components, and *t* to the twelve months prior to the month of observation of our dependent variable. To make the number of non-focal components manageable, we have defined the non-focal components at the class level instead of at the sub-class level.[2] In our measure of Local crowding, we calculate the overlap of our focal components using (1). In this case, *J* refers to the set of focal components only, while *K* denotes the set of both focal and non-focal components. Global crowding measures the overlap of our focal components with the non-focal technological components. To calculate this measure, we again use (1), but now *J* refers to the set of all non-focal components, whilst *K* is the set of all components (so both focal and non-focal).

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

[2] Strictly speaking, this implies that our non-focal components are actually composed of alternative technological systems.

number of patent citations by the density of the component. This significantly reduces the correlation between, on the one hand, component status, and, on the other hand, component density and organizational density. This implies

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

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

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

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

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

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

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

Table 1a gives the summary statistics, and Table 1b presents the correlation matrix.

--- Insert Table 1a and 1b about here ---

Organizational density, component density, and previous entries reveal high multicollinearity, which means we have to proceed with some caution.

Estimation

In ecological studies, the number of entrants is a natural and intuitive dependent variable. In organizational ecology, indeed, organizational founding studies abound.

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

(4) $\Pr(y_i \mid x_i) = \dfrac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}$ and

(5) $E(y_i \mid x_i) = \lambda_i = e^{(x_i\beta)}$,

where λ_i is the deterministic function of the covariates.

However, using the Poisson distribution for modeling economic events involves quite strong and empirically questionable assumptions (Cameron and Trivedi 1986; Cameron and Trivedi 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 and Hannan 2000). Analysis of our sample clearly demonstrates of overdispersion. [3]

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[3] If the sample variance is more than twice the sample mean, the data most likely suffer from overdispersion (Cameron and Trivedi 1998).

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

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

(6) $$\log \lambda_{it} = \beta \mathrm{X}_{it} + \gamma \varepsilon_i + \mu_i ,$$

where X_{it} is a vector of characteristics of component *i* at time *t*, γ is a correction for overdispersion, and μ_i is a time-invariant effect for each entity or component *i*, reflecting micro-level heterogeneity. This parameter can be treated as either fixed or random.

The random effects model allows for the use of both within and between-panel variance. However, the restriction for the random-effects specification is that the entity-specific term is not significantly correlated with the regressors. For this, Hausman's (1978) specification test can be used. Hausman's specification statistic is, basically, a test of the correlation between the regressors and unobserved heterogeneity or the error component in the model. The Hausman statistic is distributed as χ^2, and is computed as

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

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

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 threat to our analyses, as the majority of developments within biotechnology have taken place after the discovery of recombinant DNA in 1972. Moreover, due to changes in patent law (i.e., the so-called Bayh Doyle Act, which allows the patenting of research findings funded by means of federal grants), commercial activity within biotechnology only took off after 1980 (Sorensen and Stuart 2000). Furthermore, we have data on a cross-section of different technologies within biotechnology, implying that several new and emerging technologies are represented. Nonetheless, we should still treat our findings with some caution (Carroll and Hannan 2000).[4]

Table 2 presents estimates for the random-effects negative binomial dispersion model of patent counts. The models were estimated with the 'xtnbreg, re' command in Stata 8.0 SE. To ensure that our findings are not the result of multicollinearity, we use

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

alternative specifications to represent the density-dependent processes, and build up our baseline model incrementally using stepwise regression. In the organizational ecology literature, two models can be found to test the density dependence argument. The original model is known as the Generalized-Yule (GY) model and the alternative is called the Log-Quadratic (LQ) model. The distinction between these models is that the GY model allows for a decreasing positive effect only, while the LQ specification also allows for an increasing positive effect. According to density dependence theory, each additional entry contributes less to the legitimation of the population. Therefore, Hannan and Carroll (1992) have a preference for the GY over the LQ model, as it connects better to the original theory. They further stipulate that when GY models do not converge or when LQ models result in a much better fit, LQ models can also be used.

We thus estimate both the GY and LQ model for all our density measures (i.e., organizational density, system density, and component density), and select the specification that provides for the better fit. Even though the results of the alternative specifications are highly similar, we proceed with the GY specification for both organizational density and component density, and the LQ specification for system density. 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 χ^2 distribution with degrees of freedom equal to the number of added variables. In doing so, stability of coefficient values over alternative models increases confidence in our findings. We estimate both the GY and the LQ specification for our density measures. The parameter estimates are not standardized, which means that the coefficient values should be exponentiated before interpretation. The exponentiated coefficients represent multiplier effects on the rate of component entry.

--- Insert Table 2 about here ---

5. *Results*

Model 1 is our baseline model, including only previous entries and organizational density. Comparing the Log-likelihood value of Model 1 (-11,559) with that of Model 2 (-11,525) shows that Model 2 significantly improves model fit, as with a χ^2 of 24 (i.e., two times the difference in Log-likelihood) and three degrees of freedom, *p* is smaller than 0.01. Adding the interaction term of component status and total crowding in Model 3 does not significantly improve model fit (i.e., a χ^2 value of 0 with one degree of freedom, so $p = 0.16$).

Next, Model 4 makes a distinction between local and global crowding, significantly improving model fit. Compared to our baseline Model 1, Model 4 has a χ^2 of 74 with four degrees of freedom: Model 4 has a significantly better fit than Model 1 (i.e., $p < 0.01$). Moreover, adding the interaction terms of, on the one hand, local crowding and niche status and, on the other hand, global crowding and niche status in Model 5 significantly improves model fit further, both compared to Model 1 (i.e., χ^2 value of 80 with 6 degree of freedom, so $p < 0.01$) and to Model 4 (i.e., χ^2 value of six with two degree of freedom, so $p < 0.05$). We use Model 5 to discuss the findings.[5]

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[5] Moreover, we have also estimated Model 5 using a fixed-effects specification, and conducted Hausman's specification test to investigate the extent to which the random-effects specification is indeed appropriate. Even though this test fails to meet the asymptotic assumptions of the Hausman test, visual inspection of the coefficient values of both the fixed effects and the random effects

Hypothesis 1 is partially supported because we only find a significant positive association between component density and component entry. So, only the legitimation part of this hypothesis receives support. Increasing density from its first quartile to its median value increases component entry with 55 per cent. Further increasing component density from its median value to its third quartile increases the rate of component entry with as much as 87 per cent.

Hypothesis 2 is fully supported by our findings. We find a consistent and highly significant positive effect for system density. Even though a significant negative coefficient is found for the squared term, this only implies in a decreasing positive effect as the point of inflexion lies well outside this measure's normal range, and even above its maximum value. That is, in Model 5, the point of inflexion is -0.0806/(2*-0.0006) = 67, while the maximum value for system density is 45 (i.e., 45,000 inventions). Regarding the effect of system density, subtracting a standard deviation from its mean value reduces component entry with 112 per cent, while adding a standard deviation to its mean value increases the rate of entry with 81 per cent.

Hypothesis 3 is rejected. Instead of a positive effect, we find a significant negative effect in all models that include diversity (i.e., Models 2 to 5). In Model 5, increasing the value of component diversity with one standard deviation decreases the rate of component entry with 11 per cent.

Our analyses do substantiate Hypothesis 4. Although small, we do find a significant positive effect. Increasing the value of component status from its 1st quartile to its median value increases the rate of component entry with 3 per cent, and

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specifications reveals no large discrepancies between coefficient values under the alternative specifications.

increasing component status from its median value to its 3rd quartile increases growth with 5 per cent.

We also find full support for Hypothesis 5. As can be seen in Models 2 and 3 in Table 4, crowding does not have a significant effect on component growth until separated into its local and global representation. The coefficient for local crowding is highly significant and negative. In Model 4, increasing local crowding with one standard deviation decreases the rate of component entry with 7 per cent.

In contrast to Hypothesis 5, we do not find full support for Hypothesis 6. Even though we do have a positive coefficient for this variable, it is far from significant. However, in interaction with component status, we do find some support for the existence of positive spillovers.

Finally, Hypotheses 7 and 8 are fully supported by our estimates, as we reveal a highly significant negative coefficient for the interaction term between component status and local crowding. Moreover, the interaction between component status and global crowding is positive and highly significant.

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 discerned for the period before 1992. Although many individual years have a significant effect on niche growth, a clear evolution in either way cannot be observed. However, after 1992, a clear downward trend emerges, where each consecutive year further decreases component growth, with the exception of 1996. An in-depth investigation of this downward trend in the post-1992 period would definitely be interesting, but is outside the scope of this paper.

Next, with respect to the effect of previous entry, the coefficient for the linear term is positive and highly significant while the coefficient for the squared term is negative and highly significant, indicating a curvilinear effect of previous entry on subsequent entry. The point of inflexion (i.e., 0.18 or 180 inventions) lies well beyond this measure's normal range, implying that previous entry increases subsequent entry at a decreasing rate. Finally, as already mentioned, organizational density has a highly significant effect on component growth. Increasing organizational density from its 1st quartile to its median value increases the rate of component entry with 156 per cent, while increasing the number of organizations from its median value to its 3rd quartile further increases component entry with another 97 per cent.

6. *Discussion and conclusion*

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

First, in developing a systemic view on technological growth, we have assumed that our technological system is stable, with technological components behaving in reliable and predictable ways. In doing so, we have been able to demonstrate that biotechnology – or any other technology, for that matter – can effectively be studied as a technological system, composed of a set of interdependent and interacting technological components. However, by no means does this imply that we perceive technology as a stable system, with components behaving in reliable and predictable ways. Even though we acknowledge that some technologies could, at a certain point in time, be characterized by such a stable state, at this moment, biotechnology is most definitely not one of them. On the contrary, biotechnology can be characterized as a highly dynamic technology, with many components that are just being developed (Endy 2005; Pisano 2006). Obviously, this implies that the patterns of interactions between biotechnology's components have not yet stabilized. So, our current model is merely a steppingstone for the analysis of technology as a set of interdependent components. Our model needs to be extended to investigate the dynamics between these components over time. This could enable a distinction between the system's core and peripheral components (Tushman and Murmann 1998). In turn, this would allow for studying the evolution of a technological system, driven by the evolution of its core components (Rosenkopf and Tushman 1994).

This naturally brings us to our second point – the evolution of technological components. In contrast to our expectations, we found a significant negative effect of component diversity on component growth. This seems to point to the presence of competition between sub-components, which hampers the legitimation of the component within the larger environment. This connects to the literature on dominant designs (Utterback and Abbernathy 1975), originally conceived at the product level, but later found to be more relevant at a component level (Tushman and Murmann 1998). According to this literature, on the one hand, before a dominant design exists, actors recombine sub-components and interact socially in an effort to find or become part of the dominant configuration that will serve as the basis for the future development of the technological component. On the other hand, after a dominant design emerges, actors no longer invest in alternative configurations, but rather focus their attention on working out the sub-component configuration represented in a dominant design.

Our results point to the second stage of development, after a dominant design has been established. In this stage, additional diversity does not contribute to the legitimation of the component, but merely thwarts resources from the (explicitly or implicitly) agreed upon sub-component configuration represented by a dominant design. It thus seems that diversity, like density, plays a twin role in the evolution of a technology. 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 (Boone et al. 2004).

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

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

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

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Table 1a

Summary Statistics

Variable	Mean	SD	Min	Max	25th %	50th %	75th %
Component entry	5.017	14.354	.000	217.000	.000	1.000	4.000
Previous entry/1000	.005	.014	.000	.217	.000	.001	.004
Organizational density/1000	.034	.077	.000	.666	.001	.008	.029
Component density/1000	.669	1.628	.001	15.139	.022	.085	.571
System density/1000	16.554	11.166	2.879	44.954	7.701	12.551	22.606
Component diversity	1.827	1.496	.000	4.706	.000	1.931	3.172
Component status	.302	.710	.000	20.000	.000	.142	.384
Total crowding/1000	.077	.059	.000	.306	.029	.079	.113
Local crowding/100	.093	.081	.000	.380	.028	.081	.141
Global crowding/100	.676	.527	.000	2.714	.221	.686	.997

Table 1b

Correlation matrix

	1	2	3	4	5	6	7	8	9	10
Component entry	...									
Previous entry/1000	.93									
Organizational density/1000	.94	.94								
Component density/1000	.88	.88	.95							
System density/1000	.11	.12	.15	.10						
Component diversity	.38	.38	.46	.48	-.08					
Component status	.01	.00	.00	-.02	.17	-.06				
Total crowding/1000	-.11	-.11	-.10	-.12	.25	.10	.08			
Local crowding/100	-.08	-.08	-.07	-.11	.57	.00	.15	.82		
Global crowding/100	-.11	-.11	-.11	-.12	.20	.11	.07	.00	.77	...

Table 2

Negative binomial random-effects panel regression estimates of full model

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Previous entry/1000	8.191***	7.729***	7.728***	7.322***	7.307***
	(1.764)	(1.048)	(1.048)	(1.065)	(1.061)
$(\text{Previous entry}/1000)^2$	-22.175***	-22.254***	-22.251***	-20.760***	-20.798***
	(8.173)	(4.774)	(4.775)	(4.817)	(4.799)
LN(Organizational density)	4.581***	.546***	.546***	.544***	.543***
	(.499)	(.033)	(.033)	(.033)	(.033)
$(\text{Organizational density}/1000)^2$	-6.180***	-.217	-.218	-.297	-.315
	(.559)	(.302)	(.302)	(.304)	(.304)
System density/1000		.082***	.082***	.083***	.081***
		(.020)	(.020)	(.020)	(.020)
$(\text{System density}/1000)^2$		-.001**	-.001**	-.001**	-.001**
		(.000)	(.000)	(.000)	(.000)
LN(Component density)		.319***	.319***	.322***	.329***
		(.031)	(.031)	(.031)	(.031)
$(\text{Component density}/1000)^2$		-.034	-.032	.029	.150
		(.848)	(.851)	(.848)	(.848)
Component diversity		-.073*	-.073*	-.079*	-.080*
		(.041)	(.041)	(.041)	(.041)
Component status (CS)		.193***	.193***	.192***	.194***
		(.018)	(.020)	(.018)	(.019)
Total crowding/1000 (TC)		-.200	-.194		
		(.368)	(.412)		
Interaction: CS * TC			-.011		
			(.344)		
Local crowding/100 (LC)				-.935**	-.202
				(.444)	(.535)
Global crowding/100 (GC)				.07	-.044
				(.057)	(.073)
Interaction: CS * LC					-1.550**
					(.614)
Interaction: CS * GC					.252**
					(.102)
Constant	1.774***	-4.190***	-4.190***	-4.218***	-4.230***
	(.074)	(.458)	(.458)	(.457)	(.456)
Observations	8021	8021	8021	8021	8021
Number of components	27	27	27	27	27
Degrees of freedom	31	38	39	39	41
r	1.838	9.358	9.359	9.205	9.308
s	.769	4.353	4.353	4.283	4.352
Log likelihood	-12,353	-11,525	-11,525	-11,522	-11,519

* $p < .10$.
** $p < .05$.
*** $p < .01$